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Abstract

My Ph.D. thesis consists of three papers which are devoted to study the premia of higher moments risks, in particular, skewness risk, the relationship between stocks' higher moments and their excess returns, and the importance of higher moments of consumption risk.

In Chapter 2, I estimate skewness risk premia (SRP) on individual stocks using synthetic skew swaps and show that there is a considerably large variation of monthly realized SRP across a representative set of portfolios which are sorted by SRP in the prior period. The paper then focuses on investigating the determinants of such cross-sectional variation and documents that consumption risk does not seem to be priced with respect to SRP. The market excess return and, especially, the market variance risk premium (mVRP) are shown to be key risk factors in the cross-sectional variation of average skewness risk premium payoffs. The mVRP factor is significantly priced with respect to SRP even if I allow for potential model misspecification. The success of the mVRP factor can be potentially explained by the very different risk exposures of skewness risk premium-based portfolios to the risk proxied by the mVRP. The higher the exposure of the skewness risk premium-based portfolio to such a risk, the larger skewness risk premium payoff is required in the cross section.

In Chapter 3, I focus on exploring the relation between model-free stock implied moments and stock returns. Specifically, this paper builds an empirical model to connect option-implied cumulants with expected risk premia through latent risk factors. Expected risk premia on individual stocks are estimated by applying a new partial least squares-based method on risk-neutral cumulants at different orders and various maturities. The filtered expected risk premia based on the second and third order risk-neutral cumulants exhibit a considerably large dispersion across stocks, which further generates a wide cross-sectional variation in future realized risk premia. I find a positive relationship between the ex-ante filtered expected risk premium and future realized risk premium during the period of 1996-2017. A strategy that goes long (short) the decile portfolio with the largest (smallest) filtered expected risk premium yields a Fama-French-Carhart alpha of 1.06% per month (t-stat: 3.75). Moreover, I show that the predictive ability of the filtered expected risk premium can be potentially explained by informed trading driven by short-selling constraints.

In Chapter 4, I investigate the importance of higher moments of consumption risk in pricing cross section of stock returns. I propose a new Bayesian estimation algorithm to simultaneously estimate preferences parameters associated with higher moments of consumption risk and parameters related to consumption dynamics such that the consumption dynamics are consistent with the cross sectional variation of stock returns.

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Chapter 1

Introduction

This thesis consists of three independent but related papers which study the risk premia related to higher moments risks at the individual level, the relationship between stocks' implied higher moments and their excess returns, and the importance of higher moments of consumption risk in pricing cross section asset returns.

Since the seminal work of Kraus and Litzenberger (1976), it has been well documented that higher moments risks play an important role in the asset pricing literature over the last more than 40 years. For example, at the market level, Harvey and Siddique (2000) find that systematic skewness commands a risk premium of 3.6% per year and conditional co-skewness helps explain the cross sectional variation of expected assets returns. Agarwal et al. (2009) show that option-implied skewness of the S&P 500 index is priced in the cross-section of stock returns. Chang et al. (2013) document that stocks with high exposure to innovations in implied market skewness exhibit low returns on average. Amaya et al. (2015) find that realized skewness generates cross-sectional predictability in stock returns. In addition, at the individual level, Boyer et al. (2010) find that expected idiosyncratic skewness and returns are negatively correlated. Bali and Murray (2013) also find a strong negative relation between the risk-neutral skewness and the returns of their created delta-neutral and vega-neutral skewness assets. Conrad et al. (2013) find that more ex-ante negatively (positively) skewed returns yield subsequent higher (lower) returns. However, another strand of the literature reports a positive relationship between stock-specific skewness and future stock returns. See, for example, Rehman and Vilkov (2012), Stilger et al. (2016), and Bali et al. (2017). Given a large and still growing body evidence showing the importance of the skewness risk, it is surprising how little research analyzes skewness risk premium, especially, the skewness risk premium at the individual or portfolio level. Two exceptions are Schneider and Trojani (2015) and Pederzoli (2017). However, Schneider and Trojani (2015) focus on skewness risk premium at the market level. They propose a new class of skew swap trading strategies in incomplete market and document a positive skewness risk premium. Pederzoli (2017) analyzes the skewness risk premium on individual stocks, but she focuses on the aggregate level of individual stocks' skewness risk premium. As a supplement to the existing literature, I thoroughly analyze the skewness risk premium for individual stock in my first paper named '***The Cross-Sectional Variation of Skewness Risk Premia***'. Different from existing studies whose main focus is the price of skewness risk, my first paper contributes to the literature firstly by quantifying the size of the skewness risk premium for each individual stock contained in the S&P 500 index. Then, my paper mianly focuses on explaining the differences of skewness risk premia in the cross section across portfolios.

Specifically, I follow Kozhan et al. (2013) and estimate the skewness risk premium on individual stock with a trading strategy that replicates a skew swap whose payoffs is the difference between risk-neutral skewness and physical measure skewness. I employ daily data from OptionMetrics for the S&P 500 index options and for individual equity options on stocks included in the S&P 500 index at some point during the sample period from January 1996 through August 2015. I find that there is a considerably large variation of monthly realized skewness risk premia across a representative set of portfolios which are sorted by skewness risk premium payoffs in the prior period. I then focus on investigating the determinants of such cross-sectional variation and document that consumption risk does not seem to be priced with respect to skewness risk premia. The market excess return and, especially, the market variance risk premium are shown to be key risk factors in the cross-sectional variation of average skewness risk premium payoffs. The market variance risk premium factor is significantly priced with respect to skewness risk premia even if I allow for potential model misspecification. The success of the market variance risk premium factor can be potentially explained by the very different risk exposures of skewness risk premium-based portfolios to the risk proxied by the market variance risk premium. I further show that the higher the exposure of the skewness risk premium-based portfolio to such a risk, the larger skewness risk premium payoff is required in the cross section.

In addition to analyze the risk premium associated with higher moments risks, there is a mounting evidence that option-implied moments (both variance and higher moments) contain valuable information about future stock returns. For example, to the second moment risk, Banerjee et al. (2007) find that the VIX forecasts future stock returns of NYSE stock portfolios formed on size, book-to-market ratio and beta. Ang et al. (2006) find that the VIX is a priced factor with a negative price of risk – stocks with higher sensitivities to the innovation in VIX exhibit lower future returns on average. More recently, Martin (2017) argues that the risk-neutral variance of the market provides a lower bound on the market equity premium under mild assumptions. Martin and Wagner (2018) go one step further and provide an explicit equation of the expected risk premium on individual stocks in terms of risk-neutral variance at the market and individual levels.

For the higher moments risks, Doran et al. (2006) focus on the implied skew and find that the implied volatility skew has strong predictive power for short-term market decline. Diavatopoulos et al. (2012) document that changes in implied skewness and kurtosis prior to earnings announcements have strong predictive power for future stock and option returns. Besides, Chang et al. (2013) and Agarwal et al. (2009) show that option-implied higher moments of the S&P 500 index are also priced in the cross-section of stock returns. Although it is well-documented that option-implied higher moments are related to future stock returns, empirical studies sometimes obtain opposite findings on the relationship between risk-neutral higher moments and future stock returns. For instance, Conrad et al. (2013) find a negative relationship between option-implied skewness and the cross-section of future stock returns, while Rehman and Vilkov (2012) report a positive relationship, even though they both use the model-free skewness of Bakshi et al. (2003). Besides, consistent with the skewness preference theory, Bali and Murray (2013) also find a negative relationship between risk-neutral skewness and future equity returns. However, Stilger et al. (2016) and Bali et al. (2017) argue that the positive relationship between risk-neutral skewness and future stock returns can be explained by the demand-based option pricing model of Bollen and Whaley (2004) and Garleanu et al. (2008).

The existing studies provide strong evidence that expected stock returns are in line with option-implied moments, but it is worth pointing out that these studies usually either focus on a short-term or long-term risk-neutral moment of a specific order; hence they may miss parts of potential useful information contained in whole option price panels. Moreover, risk-neutral moments may contain returns-unrelated information that makes them not ideal as variables used directly in performing portfolio sort analysis. In my second paper, '***Risk-Neutral Cumulants, Expected Risk Premia, and Future Stock Returns***', I attempt to deal with these concerns. This study contributes to the literature in twofold. Firstly, it exploits the information contained in the whole option price panels by building an empirical model – which is consistent with the extensively studied affine reduced-form option pricing framework (see Duffie et al. (2000), Feunou et al. (2013), and Feunou and Okou (2017)) – to connect option-implied cumulants at different orders and various maturities with expected risk premia via latent risk factors. Secondly, to estimate expected risk premia on individual stocks, it proposes a new easily implementable partial least squares-based estimation procedure that exclusively extracts future returns-relevant infromation contained in risk-neutral cumulants.

Specifically, I employ risk-neutral cumulants of different orders and various maturities to condense information contained in large option price panels. Inspired by the implication of the affine reduced-form option pricing models, I assume that risk-neutral cumulants can be used to reveal underlying latent risk factors. I build an empirical model to connect option-implied cumulants with expected risk premia through latent risk factors. To efficiently filter returns-related information from a large set of risk-neutral cumulants through latent factors, I propose a partial least squares-based estimation approach, which generates consistent estimates of the infeasible best forecasts for future stock returns. Empirically, I apply the newly proposed estimation approach on the daily option prices of all stocks that have been included in the S&P 500 index during the period from 1996 to 2017. Risk-neutral cumulants are calculated for each stock using the model-free methodology of Bakshi et al. (2003). The filtered expected risk premia based on the second and third order risk-neutral cumulants exhibit a considerably large dispersion across stocks, which further generates a wide cross-sectional variation in future realized risk premia. I find a positive relationship between the ex-ante filtered expected risk premium and future realized risk premium during the period of 1996-2017. A strategy that goes long (short) the decile portfolio with the largest (smallest) filtered expected risk premium yields a Fama-French-Carhart alpha of 1.06% per month (t-stat: 3.75). Moreover, I show that the predictive ability of the filtered expected risk premium can be potentially explained by informed trading driven by short-selling constraints.

The first two papers focus on the higher moments of asset return distribution and analyze the risk premium associated with skewness risk and exploit the relation between stocks implied higher moments and their excess returns in the cross section. In my third paper, '***A Bayesian Regime Switching Model of Consumption Dynamics and the Role of Higher Moments***', I attempt to highlight the importance of higher moments of consumption risk in pricing asset returns in the cross section, which is appealing from the standpoint of economic theory. Moreover, to the best of my knowledge, this paper is the first one to thoroughly investigate the importance of higher moments of consumption growth in explaining the cross-sectional variation of asset returns.

In particular, I study the Fama and French size and book-to-market portfolios and reevaluate the central insight of the consumption-based asset pricing model that an asset's expected returns is determined by its equilibrium risk to consumption. Rather than measure the risk of a portfolio by only the contemporaneous covariance of its return and consumption growth – as done in the previous literature on the consumption-based CAPM – I measure the risk of a portfolio by also highlighting the importance of higher moments of consumption growth. I propose and estimate through Bayesian methods a flexible parametric multi-factor asset pricing model in which the importance of higher moments of consumption risk is highlighted. Moreover, the dynamics of the consumption growth are modeled as a latent regime switching process such that it is restricted by allowing the dynamics of the consumption growth to effectively explain the cross-section of U.S. stock returns. It is worth to mentioning that this framework – different from current studies – allows me to simultaneously estimate preferences parameters for higher moments of consumption risk under utility-free setting and parameters that govern consumption dynamics such that the consumption growth dynamics are consistent with the cross-section of stock returns. Ideally, the empirical results should show that the newly proposed model framework and estimation algorithm are important in the sense that this paper's setup is able to explain the cross-section of stock returns by incorporating the higher moments of consumption growth into the stochastic discount factor. More importantly, the estimated preferences parameters including risk aversion, risk prudence and risk temperance are at reasonable level and the estimated consumption dynamics are also compatible with the real data.

1.1 Structure of This PhD Thesis

As introduced above, this thesis comprises three independent but related papers. All three papers are related to the higher moments risks. I analyze the cross sectional variation of skewness risk premia in the Chapter 2. Then, Chapter 3 exploits the relation between stocks risk-neutral cumulants and their excess returns. Then, in Chapter 4, I investigate the importance of higher moments consumption risk in pricing cross section asset returns. Chapter 5 concludes the thesis.

Chapter 2

The Cross-Sectional Variation of Skewness Risk Premia

2.1 Introduction

The importance of higher order moments risk (e.g., skewness, kurtosis, and so on) for asset pricing has been highlighted by a voluminous literature in the past several decades. Among these higher order moments, skewness risk has attracted most attention for academic research.[1] Beginning with the work of Kraus and Litzenberger (1976), it has been well documented that both physical measure skewness (i.e., the realized skewness) and risk-neutral skewness play a crucial role in asset pricing.[2] Regarding asset pricing implications of the physical measure skewness, for example, Harvey and Siddique (2000) find that systematic skewness helps explain the cross section of returns. Bakshi and Madan (2006) and Chabi-Yo (2012) show theoretically that skewness of the market index is a key factor of the market variance risk premium. Recently, Amaya et al. (2015) find that realized skewness generates cross-sectional predictability in stock returns. Jondeau et al. (2018) show that average skewness preforms well at predicting future market returns. On the other hand, the risk-neutral skewness has also been extensively studied in asset pricing since the seminal works of Bakshi and Madan (2000) and Bakshi et al. (2003). Several representatives are Rehman and Vilkov (2012), Conrad et al. (2013), Chang et al. (2013), Stilger et al. (2016),

[1] In industry, similar to the VIX index, the Chicago Board Options Exchange (CBOE) published the Skew Index (ticker: SKEW) in 2011, which is viewed as a benchmark measure of the perceived risk of extreme negative moves – often referred to as tail risk or a black swan event – in the U.S. equity markets.

[2] In addition to asset pricing implications of the skewness risk, it is also very important for portfolio and risk management. See, for example, Brunnermeier et al. (2007), Barberis and Huang (2008), Mitton and Vorkink (2007), Guidolin and Timmermann (2008), Boyer et al. (2010), Giamouridis and Skiadopoulos (2009) and references therein.

and Bali et al. (2017). Given a large and still growing body evidence showing the importance of the skewness risk, it is surprising how little research analyzes skewness risk premium, especially, the skewness risk premium at the individual or portfolio level. Two exceptions are Schneider and Trojani (2015) and Pederzoli (2017). However, Schneider and Trojani (2015) focus on skewness risk premium at the market level. They propose a new class of skew swap trading strategies in incomplete market and document a positive skewness risk premium. Moreover, they show that skew swaps appear as the most appropriate vehicles for trading fear and disaster risk. Pederzoli (2017) analyzes the skewness risk premium on individual stocks, but she focuses on the aggregate level of individual stocks' skewness risk premium. Different from existing studies whose main focus is the price of skewness risk, this paper contributes to the literature firstly by quantifying the size of the skewness risk premium. Then, this paper mianly focuses on explaining the differences of skewness risk premia in the cross section. Specifically, I investigate skewness risk premia on individual stocks with a newly proposed method of Kozhan et al. (2013) and further analyze the determinants of the cross-sectional variation of realized skewness risk premia across portfolios.

In particular, I follow Kozhan et al. (2013) and estimate the skewness risk premium (SRP) on individual stock with a trading strategy that replicates a skew swap whose payoffs is the difference between risk-neutral skewness and physical measure skewness. Specifically, I employ daily data from OptionMetrics for the S&P 500 index options and for individual equity options on 1002 stocks included in the S&P 500 index at some point during the sample period from January 1996 through August 2015. I concentrate on 30-day horizon (monthly) SRP, calculated by the method suggested by Kozhan et al. (2013). In each month, I sort securities into 20 portfolios by their estimated SRP levels. Then these portfolios are held over the next month and their realized equal-weighted SRP are calculated. The ranking procedure is updated monthly. In the meanwhile, the market skewness risk premium (mSRP) is also calculated by using the options written on the S&P 500 index. Firstly, at the market level, I show that the average monthly mSRP is -0.475, which is consistent with the findings in the previous literature such as Bakshi et al. (2003) and Kozhan et al. (2013). Kozhan et al. (2013) report an average monthly mSRP at -0.421.[1] The negative mSRP means that the writer of a skew swap who receives fixed and pays floating on average loses money, indicating that risk-averse investors are willing to accept negative returns for hedging against a drop in skewness risk. Secondly, at the portfolio level, I show that there is a considerably large variation of the average monthly realized SRP across 20 portfolios, ranging increasingly from -1.85 for portfolio 1 to 0.50 for portfolio 20. It is worth mentioning that 19 of 20 portfolios earn on

[1]Kozhan et al. (2013) also point out that the negative market skewness risk premium, -0.421, indicates that 42.1% of the implied skew in index option prices can be explained by the risk premium.

average a negative SRP. Moreover, I document a significant difference of SRP between the portfolio and the market index, which in turn supports the necessity of investigating the behavior of SRP at the individual or portfolio level.

To explain the cross-sectional variation of SRP across 20 portfolios, I focus on two types widely studied model specifications: (1) consumption-based stochastic discount factor (SDF) specifications and (2) factor-based SDF specifications. The empirical tests show that consumption risk under either the power utility or the recursive preferences does not seem to be priced in the cross section with respect to SRP. However, factor-based asset pricing models perform well in explaining the cross-sectional variation of skewness risk premium payoffs across portfolios. In particular, the two-factor asset pricing specification with the market variance risk premium ($mVRP$) and the market excess return (Rm) as risk factors is not statistically rejected. Both factors, especially, the $mVRP$ factor is significantly priced in the cross section with respect to SRP even if I explicitly recognize the potential misspecification of the tested models and the errors-in-variables (EIV) issues. Specifically, the selected two-factor model with the $mVRP$ and the Rm as factors generates a substantially large cross-sectional R^2 at 36.1%, which is significantly different from zero. Finally, I provide an intuitive but rigorous explanation to the main findings of the paper and show that the success of the $mVRP$ factor in the cross-sectional variation of SRP can be potentially explained by the very different risk exposures of skewness risk premium-based portfolios to the risk proxied by the $mVRP$.[1] Moreover, I show that the higher the exposure of the skewness risk premium-based portfolio to such a risk, the higher skewness risk premium payoff is required by investors in the cross section, which is consistent with the classical idea of risk-return trade-off.

2.1.1 Related Literature

This study relates to different strands of the literature. First of all, it contributes to the literature that analyzes the price of skewness risk. At the market level, a voluminous literature has explored the importance of skewness risk for asset pricing since the mid-2000s. For example, Harvey and Siddique (2000) propose an asset pricing model to incorporate conditional skewness and show that conditional systematic skewness helps explain the cross-sectional variation of expected stock returns. Bakshi and Madan (2006) document that skewness of the underlying market index is related to the market variance risk premium. In addition, Agarwal et al. (2009) show that option-implied skewness of the S&P 500 index is also priced in the cross-section of stock returns. Recently, Feunou et al. (2011)

[1] It is worth mentioning that the market variance risk premium is also priced in the cross section of stock returns as well as in the cross section of volatility risk premia. See, for example, Han and Zhou (2012), González-Urteaga and Rubio (2016), Feunou et al. (2017), among others.

show that accounting for skewness is important to identify the sign of the risk-return relation. Chang et al. (2013) document that stocks with high exposure to innovations in implied market skewness exhibit low returns, on average. Moreover, Amaya et al. (2015) find that realized skewness generates cross-sectional predictability in stock returns.

In addition to the market skewness, stock-specific skewness has also been studied extensively in asset pricing. For example, Boyer et al. (2010) and Conrad et al. (2013) report a negative relationship between stock-specific skewness and future stock returns. Similar pattern is also found by Bali and Murray (2013). Moreover, these results support the skewness preference theory. However, another strand of the literature reports a positive relationship between stock-specific skewness and future stock returns. See, for example, Rehman and Vilkov (2012), Stilger et al. (2016), and Bali et al. (2017). Furthermore, they argue that such positive relationship can be explained by the demand-based option pricing model of Bollen and Whaley (2004) and Garleanu et al. (2009). Different from this literature whose main focus is the price of skewness risk, the goal of this study is to quantify the size of the skewness risk premium.

Secondly, this study is also closely related to the literature that explores the risk premia related to different moments of asset return distribution. For example, a voluminous literature has documented the existence of a positive first-moment risk premium, i.e., positive equity risk premium (see, e.g., Fama and French (1993), Carhart (1997), Fama and French (2015), among others). The seminal work of Bakshi et al. (2003) has inspired the investigation of the risk premia associated with higher moments of the return distribution, particularly the variance risk premium (see, e.g., Ang et al. (2006), Carr and Wu (2009), Bollerslev et al. (2009), González-Urteaga and Rubio (2016), among others). Besides, regarding premium related to the skewness risk, Eraker (2008) and Kozhan et al. (2013) show theoretically and empirically that it is highly correlated with volatility risk premium, respectively. Moreover, Kozhan et al. (2013) document a negative skewness risk premium for the market index. Recently, Rauch and Alexander (2016) show that the market skewness risk premium only highly correlated with the market variance risk premium at low sampling frequency, but it is highly associated with the market kurtosis risk premium regardless of the sampling frequency. Sasaki (2016) examines the predictability of the market skewness risk premium and finds that it has superior predictive power to future market index returns. My paper contribute to this strand of the literature by extending the studies on the first and second moment risk premium to the third moment risk premium. Moreover, unlike Kozhan et al. (2013), who only analyze the skewness risk premium on the S&P 500 index, this paper investigates skewness risk premia on individual stocks and further conducts a thorough cross-sectional analysis.

The rest of the paper is organized as follows. Section 2.2 describes the stochastic discount factor specifications tested in the cross-sectional variation of skewness risk premia. Section 2.3 introduces the details of the data and the synthetic skew swaps used for measuring skewness risk premia. Section 2.4 presents characteristics of skewness risk premia across stocks. The discussion of the testing strategy and the main empirical findings are reported in Section 2.5. Section 2.6 shows the results of robustness checks. In Section 2.7, I provide an intuitive explanation to the main findings. Section 2.8 concludes the paper.

2.2 The Analytical Framework

In this paper, I focus on inferring skewness risk premia (SRP) on individual stocks. Specifically, I follow Kozhan et al. (2013) and calculate SRP for each stock from a synthetic skew swap. After that, I mainly focus on investigating the determinants of the cross-sectional variation of SRP. The details of the calculation of SRP are postponed to the following Section 2.3. I explain in this part the theoretical framework used in this paper to analyze the cross-sectional variation of skewness risk premia across stocks.

Denote the τ-period skewness risk premium of stock i at time t as $SRP^i_{t,t+\tau}$, and then the fundamental asset pricing framework implies that

$$E_t(M_{t,t+\tau} SRP^i_{t,t+\tau}) = 0 \tag{2.1}$$

where $M_{t,t+\tau}$ is the stochastic discount factor (SDF). To empirically explore why SRP exhibits large variation across stocks, equation (2.1) implies that we should analyze as many models as possible and examine a full battery of stochastic discount factor specifications. However, analyzing all model or SDF specifications, on the one hand, is impossible. On the other hand, it also makes us have a trouble of model proliferation. To balance the potential danger of model proliferation with a parsimonious approach to present the most informative and robust results about the cross-sectional variation of SRP, I concentrate on two types extensively tested model/SDF specifications in this paper: (1) consumption-based model specification and (2) factor-based model specification.[1] In addition, as pointed out by Harvey et al. (2016), to make a new proposed factor to be accepted as a reasonable and trustable risk factor, it usually needs a higher hurdle with t-ratio larger than 2.0. To deal with this concern, I report not only the traditional test statistics but also the model-misspecification adjusted test statistics to make sure the newly proposed factor is indeed helpful in explaining the cross-sectional variation of SRP across stocks.

[1]Both consumption-based and factor-based model specifications have been shown by a large number of studies are useful in explaining at least the cross-sectional variation of stock returns. Harvey et al. (2016) partially summarizes the huge literature in this field.

Under the consumption-based model framework, in order to generate at least from the time series perspective the realistic dynamics of the higher-order moment risk premium, we usually assume the representative agent is equipped with power utility or recursive preferences with stochastic or uncertainty process for consumption growth and/or for volatility of consumption growth.[1] Therefore, the first type SDF analyzed in this paper are derived from either the power utility or the Epstein-Zin recursive preferences. It is worth mentioning that I focus on linear expressions of SDF specifications in the following empirical analysis. In addition to the consumption-based specifications, I also examine the factor-based models. Specifically, I employ linear SDF specifications based on the state variables capable of explaining the SRP at least at the market level.

Consumption-Based SDF Specifications

I start SDF specifications from consumption-based models.[2] The first SDF specification I consider is derived from the power utility:

$$M_{t,t+1} = \beta \frac{U'(C_{t+1})}{U'(C_t)} = \beta (\frac{C_{t+1}}{C_t})^{-\gamma} \tag{2.2}$$

where C_t is the personal aggregate consumption, β denotes the subjective discount factor, and γ equals to the degree of risk aversion.[3]

Although the power utility setup was widely used in the asset pricing literature in the early time, it is well-known that the power utility setup is unable to explain financial market puzzles like equity premium puzzle unless with an unreasonable high risk aversion or incorporate for example ambiguity or learning into the model. In this case, a new recursive preferences setup is proposed by Epstein and Zin (1989), which has been extensively studied and shown that it has better performance than the power utility function in explaining asset price anomalies. Therefore, the second SDF is derived from the recursive preferences:

$$U_t = [(1-\beta)C_t^{1-\rho} + \beta(E_t(U_{t+1}^{1-\gamma}))^{\frac{1-\rho}{1-\gamma}}]^{\frac{1}{1-\rho}}$$

[1] In the Lucas economy with power utility, Leippold et al. (2008) show that the joint presence of learning and ambiguity enforces large equity premia, and Buraschi et al. (2014) find that the cross-sectional variation of volatility risk premia can be explained by incorporating heterogenous beliefs into a Lucas orchard.

[2] Yogo (2006) shows that durable and nondurable consumption growth explain both the cross-sectional variation of expected stock returns and the time-series dynamics of the equity premium, and Jagannathan and Wang (2007) find that when consumption betas of stocks are computed using year-over-year consumption growth based upon the fourth quarter, the consumption-based capital asset pricing model explains the cross section of stock returns.

[3] In empirical part, I also use personal aggregate consumption of non-durable goods and services as a substitute, and the results are qualitatively similar.

and then the SDF is given by

$$M_{t,t+1} = (\beta(\frac{C_{t+1}}{C_t})^{-\rho})^{\frac{1-\gamma}{1-\rho}}(\frac{1}{U_{t+1}})^{\frac{\gamma-\rho}{1-\rho}} \tag{2.3}$$

where $1/\rho$ denotes the elasticity of intertemporal substitution.[1] Since the continuation value is non-observable, I use two methods to estimate the latent continuation value in practice. First, I follow Epstein and Zin (1991) and use the market return as an approximation. Second, I follow Thimme and Völkert (2015) and calculate the return on the wealth portfolio with the following equation

$$R^{cay}_{t,t+1} = \frac{C_{t+1}}{C_t}\frac{exp(cay_t - cay_{t+1})}{1 - \kappa * exp(cay_t)}$$

where *cay* approximates innovations in the log consumption-wealth ratio and it is defined by Lettau and Ludvigson (2001), and κ is set to yield an average consumption-wealth ratio of about 1/25 in annual terms, which is in line with the value given in Lettau and Ludvigson (2001).

Factor-Based SDF Specifications

Except the consumption-based SDF specifications, I next turn to the SDF based on the factor-based model specifications. Bakshi et al. (2003) and Bakshi and Madan (2006) show that the time-series dynamics of skewness risk premium (SRP) can be explained by higher moments of the log returns, suggesting that a potential relevant model to explain the cross-sectional variation of SRP should also explicitly recognize the higher-order moments of the underlying market returns.[2] In this case, to capture the effects of the higher moments, I assume that the first factor-based SDF is a linear function of the market return and its high-order moments. Specifically, for higher-order moments, I use either the squared realized return or the option-implied higher-order moments which are calculated with the model-free method proposed by Bakshi et al. (2003).[3]

$$M_{t,t+1} = a + b \cdot R_{m,t+1} + c \cdot R^2_{m,t+1} \tag{2.4}$$

$$M_{t,t+1} = a + b \cdot R_{m,t+1} + c \cdot IV_{m,t+1} + d \cdot ISKEW_{m,t+1} + e \cdot KS_{m,t+1} \tag{2.5}$$

[1] Using consumption growth and the return on the wealth portfolio to represent the pricing kernel in practice is also suggested by Ju and Miao (2012).

[2] Dittmar (2002) also shows that nonlinear pricing kernel – SDF is a nonlinear function of wealth return – is useful in explaining the cross section of equity returns.

[3] Rauch and Alexander (2016) find that the premia to the skewness risk and to the kurtosis risk are highly correlated, which may also imply that the market kurtosis is a potential factor for the cross sectional variation of skewness risk premia. Moreover, Bakshi et al. (2003) show in their Theorem 2 that the skewness risk premium is a function of kurtosis of the returns. Besides, Gormsen and Jensen (2017) also show that the higher moment risks are usually correlated with each other.

where $R_{m,t+1}$ is the market excess return, $IV_{m,t+1}$, $ISKEW_{m,t+1}$ and $KS_{m,t+1}$ are option-implied variance, skewness and kurtosis calculated directly from option prices on the S&P 500 index, respectively.

The capital asset pricing model (CAPM) shows that market-wide risk is often predicted as a determinant of the market equity premium. Recently, several studies such as Ang et al. (2006), Adrian and Rosenberg (2008), and Chang et al. (2013) have shown that market-wide risk is also priced in the cross section of stock returns. Based on these evidence, plus the finding that the market skewness is an important indicator of market-wide risk, it seems reasonable to assume that the market skewness risk premium (mSRP) includes some explanatory power to the cross-sectional variation of SRP across stocks.[1] Moreover, adding the information from the index option market into pricing kernel is also suggested by Vanden (2004) and Vanden (2006).[2] Therefore, the second and third factor-based SDF specifications are assumed to be a linear function of the mSRP.

$$M_{t,t+1} = a + b \cdot mSRP_{t+1} \tag{2.6}$$

$$M_{t,t+1} = a + b \cdot R_{m,t+1} + c \cdot mSRP_{t+1} \tag{2.7}$$

where $mSRP_{t+1}$ is the market skewness risk premium calculated based on the options written on the S&P 500 index.

Eraker (2008) and Kozhan et al. (2013) show theoretically and empirically that variance risk premium is tightly related with skewness risk premium, respectively. In addition, market variance or volatility risk premium has been empirically proven useful in explaining both the cross-sectional variation of volatility risk prima and the cross section of equity returns (see González-Urteaga and Rubio (2016) and Bali and Zhou (2016)). Hence, in the fourth and fifth factor-based SDF specifications, I consider both the market skewness risk premium (mSRP) and the market variance risk premium (mVRP) as pricing factors. In particular, the SDF specifications are given by

$$M_{t,t+1} = a + b \cdot mSRP_{t+1} + c \cdot mVRP_{t+1} \tag{2.8}$$

$$M_{t,t+1} = a + b \cdot R_{m,t+1} + c \cdot mSRP_{t+1} + d \cdot mVRP_{t+1} \tag{2.9}$$

[1] As one kind of market-wide risk, both realized skewness and implied skewness have been found useful in explaining the cross-sectional variation of stock returns (see Agarwal et al. (2009), Boyer et al. (2010), Amaya et al. (2011), Xing et al. (2010), Conrad et al. (2013), Chang et al. (2013), among others).

[2] Vanden (2004) and Vanden (2006) study asset pricing in an equilibrium setup with non-negative wealth constraints and show that in the presence of these constraints, the pricing kernel is a function of the market index return, the return on market index options and their higher-order powers.

where $mVRP_{t+1}$ is the market variance risk premium calculated based on the options written on the S&P 500 index. Again, the detail of the calculation of $mVRP_{t+1}$ is delayed to the following Section 2.3.

In addition to the aforementioned specifications, I also test specifications with widely studied potential macroeconomic factors such as the default risk premium factor Def_t, defined as the difference between Moody's yield on Baa corporate bonds and the ten-year government bond yield, which is proposed by González-Urteaga and Rubio (2016) containing significant explanatory power to the cross-sectional variation of volatility risk premia; the spread factor Ted_t, defined as the spread between three-month LIBOR and three-month U.S. Treasury-bill rate at the beginning of month t, which is suggested by Kozhan et al. (2013) who show that it can be used to explain the market skewness risk premium. Moreover, the extensively studied factors such as the Fama and French (1993) three factors, the Fama and French (2015) five factors, and the momentum factor proposed by Carhart (1997) are also investigated in this paper.

2.3 Data and Methodology

I describe in this section the data and method used to calculate skewness risk premia for the market index and individual equities, which are then used for the following cross-section analysis.

2.3.1 Data

The sample used in this paper combines different data sources and covers the period from January 1996 through August 2015. In particular, options data are obtained from the OptionMetrics Ivy DB database (provided through Wharton Research Data Services). I employ daily data of the S&P 500 index options and of individual options on all stocks included in the S&P 500 index at some point, which yields a total of 1002 stocks used in this paper. Options mature every month. I select all put and call options on individual stocks and on the S&P 500 index with time to maturity between 6 days and 60 days. Given the options written on individual stocks are American style, it is convenient to work with short-term maturity options, for which the early exercise premium tends to be negligible.[1]

For each stock or market index, the data set includes closing bid and ask quotes for each option contract and I adopt the average of bid and ask prices

[1] Analyzing short-term maturity options to mitigate the effect of early exercise premium is widely used in the literature, see for example, Driessen et al. (2009), González-Urteaga and Rubio (2016), and among others. Besides, focusing only on the short-term maturity data also makes the size of sample controllable.

to calculate the mid-quotes to avoid the well-known bid-ask bounce problem described by Bakshi et al. (1997). Following convention, several regular filters are implemented to construct the final sample used in the paper. First, I filter out all contracts with nonstandard settlements. Second, I discard options with zero open interest and zero bid price. Third, I eliminate options with negative implied volatility. Fourth, options with missing implied volatility or delta are also ignored. Finally, I follow Chang et al. (2013) and exclude in-the-money options when calculating risk-neutral moments due to their less liquid compared to out-of-the-money and at-the-money options. Specifically, I eliminate put options with strike price of more than 103% of the underlying asset price ($K/S > 1.03$) and call options with strike price of less than 97% of the underlying asset price ($K/S < 0.97$). In addition to the option data, the daily returns of the underlying stocks and the daily market return for the S&P 500 index are also obtained from OptionMetrics.

Besides, the monthly aggregate consumption expenditures, and the data of consumption expenditures for nondurable goods and services are all downloaded from the webpage of the Federal Reserve Bank of St. Louis.[1] To compute consumption per capita, I collect the U.S. population data from the United States Census Bureau, where it provides monthly population estimates of the U.S.[2] The quarterly *cay* data is available at Martin Lettau's personal webpage.[3] Besides, the spread between the three-month LIBOR and the three-month U.S. Treasury-bill rate, Ted_t, and the daily yields for Moody's Baa corporate bonds and 10-year Treasury Constant Maturity are also downloaded from the webpage of the Federal Reserve Bank of St. Louis. The default risk premium Def_t is defined as the difference between Moody's yield on Baa corporate bonds and the 10-year Treasury Constant Maturity yield. In addition, the monthly risk-free rate, the Fama-French five factors (Fama and French (2015)), and the Momentum factor (Carhart (1997)) are obtained from Kenneth French's webpage.[4]

2.3.2 Methodology

When dealing with higher-order moments risk, one challenge facing researchers is the difficulty in constructing hedge portfolios for these higher moments risk. Following Bakshi et al. (2003) and Carr and Wu (2009), Kozhan et al. (2013) develop a methodology to measure risk premium in any desired moment of returns.[5] In

[1] `https://www.stlouisfed.org/`

[2] `https://www.census.gov/en.html`

[3] `http://faculty.haas.berkeley.edu/lettau/data_cay.html`

[4] `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

[5] Bakshi et al. (2003) show theoretically how to compute the standard deviation, skewness, and kurtosis of the risk-neutral density function from portfolios of options that replicate moments of returns and compare these risk-neutral statistics with the corresponding statistics of

particular, the risk premium is defined as the expected profit by implementing a trading strategy which has an interpretation as a synthetic swap contract, where the fixed leg is the option-implied moment and the floating leg is the realized moment. In this paper, I follow Kozhan et al. (2013) and the skewness risk premium is defined as the expected profit from a self-financing trading strategy, which is a pure bet on the desired return moments.[1] Specifically, the skewness risk premium is calculated from synthetic skew swap.

2.3.2.1 Skew Swap

The methodology of Kozhan et al. (2013) has two key features. First, it is a trading strategy that has an interpretation as skew swap, so the expected profit from this strategy can be certainly interpreted as a risk premium. Second, because the mark-to-market value of the strategy perfectly hedges changes in the implied moment, the average profit from the strategy can be regarded as the premium for being exposed to the risk represented by that moment. To measure skewness risk premium, I follow Kozhan et al. (2013) to construct a skew swap. Consider a payoff function $g^S(r_{t,T}) = 6(2+r_{t,T}-2e^{r_{t,T}}+r_{t,T}e^{r_{t,T}})$, where $r_{t,T}$ is the log return of the forward from time t to T. Kozhan et al. (2013) show that the g^S-swap reflects skewness (see Proposition 2 of their paper) and the fixed leg $G^S_{t,T}$ is given by

$$G^S_{t,T} = E^Q_t[6(\frac{F_{T,T}}{F_{t,T}}+1)ln(\frac{F_{T,T}}{F_{t,T}}) - 12(\frac{F_{T,T}}{F_{t,T}}-1)] \tag{2.10}$$

where $F_{t,T}$ is the price at time t of a forward contract with maturity at T. Moreover, G_S can be written as the difference between the implied Black-Scholes variances of two contracts: the log contract with payoff function $g^L(r_{t,T}) = 2(e^{r_{t,T}} - 1 - r_{t,T})$ and the entropy contract with payoff function $g^E(r_{t,T}) = 2(r_{t,T}e^{r_{t,T}} - e^{r_{t,T}} + 1)$. The fair price of these two contracts are given by

$$G^L_{t,T} = 2E^Q_t[\frac{F_{T,T}}{F_{t,T}} - 1 - ln(\frac{F_{T,T}}{F_{t,T}})] \tag{2.11}$$

$$G^E_{t,T} = 2E^Q_t[\frac{F_{T,T}}{F_{t,T}}ln(\frac{F_{T,T}}{F_{t,T}}) - \frac{F_{T,T}}{F_{t,T}} + 1] \tag{2.12}$$

---

the physical distribution of daily returns. Carr and Wu (2009) examine the profitability of variance swaps, where the investor holds a portfolio of options across all strikes, and show that there is a substantial risk premium in the level of implied volatility averaged across all strikes.

[1] In practice, the trading strategy used in this paper involves buying low-strike puts and writing high-strike calls and subsequently trading options and forwards on the underlying.

Then, the fixed leg $G^S_{t,T}$ can be re-written as

$$G^S_{t,T} = 3(G^E_{t,T} - G^L_{t,T}) \tag{2.13}$$

Implied Skewness

Based on the work of Bakshi et al. (2003), Kozhan et al. (2013) show that the log contract (equation (2.11)) and the entropy contract (equation (2.12)) can be replicated by European options. Specifically, they can be calculated with the following formulae. The interested readers are suggested to Kozhan et al. (2013) for details.

$$IV^L_{t,t+\tau} = 2\sum_{K_i \le F_{t,t+\tau}} \frac{P_{t,t+\tau}(K_i)}{B_{t,t+\tau}K_i^2}\Delta I(K_i) + 2\sum_{K_i > F_{t,t+\tau}} \frac{C_{t,t+\tau}(K_i)}{B_{t,t+\tau}K_i^2}\Delta I(K_i) \tag{2.14}$$

$$IV^E_{t,t+\tau} = 2\sum_{K_i \le F_{t,t+\tau}} \frac{P_{t,t+\tau}(K_i)}{B_{t,t+\tau}K_iF_{t,t+\tau}}\Delta I(K_i) + 2\sum_{K_i > F_{t,t+\tau}} \frac{C_{t,t+\tau}(K_i)}{B_{t,t+\tau}K_iF_{t,t+\tau}}\Delta I(K_i) \tag{2.15}$$

where $\Delta I(K_i)$ is the changing of strikes defined as

$$\Delta I(K_i) = \begin{cases} \dfrac{K_{i+1} - K_{i-1}}{2}, & for\ 0 \le i \le N, with\ K_{-1} = 2K_0 - K_1, K_{N+1} = 2K_N - K_{N-1} \\ 0, & otherwise \end{cases}$$

and $P_{t,t+\tau}(K_i)$ ($C_{t,t+\tau}(K_i)$) is the price at time t of a put (call) option that matures at $t+\tau$ with strike K_i. K_i is one of the $N+1$ different traded strike prices, which are ordered increasingly from K_0 to K_N. $F_{t,t+\tau}$ is the price at time t of a forward contract with maturity $t+\tau$, and $B_{t,t+\tau}$ is the price of a bond at time t with $B_{t+\tau,t+\tau} = 1$. $IV^L_{t,t+\tau}$ ($IV^E_{t,t+\tau}$) is used to denote the implied variance computed from a log contract (entropy contract). As claimed by Kozhan et al. (2013), using the above formulas to calculate implied variance is standard (e.g., Bollerslev et al. (2009)). However, some papers use an alternative method to interpolate and extrapolate volatilities (e.g., Carr and Wu (2009), Chang et al. (2013), and González-Urteaga and Rubio (2016)). In Section 2.6, I analyze variances obtained from this alternative approach to do a robustness check.

Based upon the equations (2.14) and (2.15), the implied skewness, $ISKEW_{t,t+\tau}$, is computed by

$$ISKEW_{t,t+\tau} = \frac{3(IV^E_{t,t+\tau} - IV^L_{t,t+\tau})}{(IV^L_{t,t+\tau})^{3/2}} \tag{2.16}$$

For each time to maturity τ from 6 to 60 days, I calculate the model-free implied skewness each day for each underlying asset that has at least three available options outstanding, using all the available options at time t.

Realized Skewness

To infer the floating leg of the skew swap, Kozhan et al. (2013) show that the payoff functions ($g^S(r_{t,t+\tau})$ and $g^L(r_{t,t+\tau})$) have the aggregation property and the realized moments related to them can be calculated easily (see equations (7) and (16) in Kozhan et al. (2013)). Specifically, the realized variance $RV_{t,t+\tau}$ (corresponds to $g^L_{t,t+\tau}$) and skewness $RS_{t,t+\tau}$ (corresponds to $g^S_{t,t+\tau}$) are computed by the following equations[1]

$$RV_{t,t+\tau} = \sum_{i=t}^{t+\tau-1} [2(e^{r_{i,i+1}} - 1 - r_{i,i+1})] \tag{2.17}$$

$$RS_{t,t+\tau} = \sum_{i=t}^{t+\tau-1} [3\delta IV^E_{i,t+\tau}(e^{r_{i,i+1}} - 1) + 6(2 - 2e^{r_{i,i+1}} + r_{i,i+1} + r_{i,i+1}e^{r_{i,i+1}})] \tag{2.18}$$

where $r_{t,t+\tau} = log(F_{t+\tau,t+\tau}) - log(F_{t,t+\tau})$ and $\delta IV^E_{t,t+\tau}$ is the changing of the value of the implied variance from entropy contract $IV^E_{t,t+\tau}$, i.e., $\delta IV^E_{t,t+\tau} = IV^E_{t+\delta,t+\tau} - IV^E_{t,t+\tau}$. The realized skewness $RSKEW_{t,t+\tau}$ is defined as

$$RSKEW_{t,t+\tau} = \frac{RS_{t,t+\tau}}{(IV^L_{t,t+\tau})^{3/2}} \tag{2.19}$$

2.3.2.2 Skewness Risk Premium

As pointed out by Kozhan et al. (2013), the trading strategy developed in their paper can be interpreted as a synthetic skew swap contract. The skewness risk premium (profit per \$1 investment in the fixed leg) obtained by implementing such a trading strategy can be expressed by the fixed leg (equation (2.16)) and the floating leg (equation (2.19)) of the skew swap. In particular, the τ-period skewness risk premium $SRP_{t,t+\tau}$ is given by

$$SRP_{t,t+\tau} = RSKEW_{t,t+\tau}/ISKEW_{t,t+\tau} - 1 \tag{2.20}$$

Similarly, the τ-period variance risk premium $VRP_{t,t+\tau}$ is given by

$$VRP_{t,t+\tau} = RV_{t,t+\tau}/IV^L_{t,t+\tau} - 1 \tag{2.21}$$

Using equation (2.20) to calculate skewness risk premium goes well beyond the existing literature, which has contrasted the average implied distribution of period returns from option prices with the observed distribution of daily returns

[1] For the definition details of the floating leg of the skew swap, I refer interested readers to Neuberger (2012).

(e.g., Bakshi et al. (2003)). Kozhan et al. (2013) point out that even though the difference between the two may suggest the presence of risk premium, it falls well short of conclusive evidence. For instance, in a Heston model without risk premium, the distribution of high-frequency returns is unskewed both conditionally and unconditionally, but the implied distribution of period returns exhibits a pronounced skew if shocks to returns and volatility are correlated.

For empirical analysis, I employ the same horizon skewness risk premium. Specifically, at each time t, I calculate 30-day ($\tau = 30$) horizon skewness risk premium, and if necessary, the 30-day horizon skewness risk premium is computed by using interpolated or extrapolated 30-day horizon implied as well as realized variance with the nearest maturities τ_1 and τ_2 following the procedure of Carr and Wu (2009). In other words, I calculate the 30-day horizon implied and realized variance in the first step, and then I employ the above introduced formulas (equations (2.16)-(2.20)) to compute the 30-day horizon skewness risk premium. In particular, the 30-day horizon implied (realized) variance can be interpolated by

$$VAR_{t,t+\tau} = \frac{VAR_{t,t+\tau_1}\tau_1(\tau_2 - \tau) + VAR_{t,t+\tau_2}\tau_2(\tau - \tau_1)}{\tau(\tau_2 - \tau_1)}$$

where VAR denotes either implied variance or realized variance.

2.4 Skewness Risk Premium Characteristics

In this paper, I concentrate on trading strategies that run for a month. The skewness risk premium (SRP) in each month is defined as the mean of the daily skewness risk premium within that month. Note that the SRP has a fixed 30-day maturity. I focus on SRP at the portfolio level instead of the individual level. To construct portfolios, I sort securities into 20 portfolios based on their SRP in each month. In particular, portfolio 1 includes the securities with the lowest SRP levels while portfolio 20 contains the highest ones. All 20 portfolios have approximately the same number of securities, with an average of 17.7 securities per portfolio. These portfolios are held over the next month and then their equal-weighted realized SRP are computed. Table 2.1 reports the characteristics of these 20 SRP level-sorted portfolios.

[Table 2.1 about here]

The column 1 shows that on average, the monthly realized SRP exhibits a considerably large variation across portfolios, ranging from -1.86 for P1 to 0.50 for P20. Moreover, the negative SRP for the market index ($mSRP$), -0.48, is also consistent with the findings in the previous literature such as Bakshi et al. (2003), Kozhan et al. (2013), and Chang et al. (2013).[1] The negative SRP means that the writer of a skew swap who receives fixed and pays floating generally receives and pays negative amounts and on average loses money. In addition, if we move to the Median (fifth column), the average monthly realized SRP levels display a similar pattern, with the range going from -0.95 for P1 to -0.28 for P20. In any case, we can conclude that the cross-sectional difference of SRP on average is large and seems to justify the study of their determinants. Given SRP is in general interpreted as a compensation for downside risk or disaster risk (see e.g., Schneider and Trojani (2015), Pan (2002), among others), I tend to identify the purchase of skewness as a hedging instrument against potentially stock market crash. In this case, the differences of the SRP across portfolios indicate that investors can have very different investment vehicles depending on whether they go long or short on skewness of different portfolios. The standard deviations (SD) of the monthly realized SRP of 20 portfolios reported in the second column suggest that the portfolios with higher average SRP in magnitude are the more volatile portfolios.

In order to check whether the variation of the realized SRP in different portfolios are related to the stocks performances, I calculate the equal-weighted stock returns for these 20 SRP level-sorted portfolios. The results are shown in the fourth column of Table 2.1, indicating that there is no big difference of stocks' performances across portfolios except the portfolio 20 whoes stock return is relatively smaller compared to all other portfolios. Next, in the six and seventh columns, I report the average trading volumes of stocks ($Vstock$) and the relative bid-ask spread of the options (BAS) associated with the constituents of 20 portfolios, respectively. The concern here is the replication costs of the skew swaps across portfolios. If the stock and/or options traded on the constituents of portfolios with high absolute average SRP values are extremely illiquid, then the replicating strategy used to obtain synthetic skew swaps may be more expensive than in other portfolios with more liquid traded constituents. In this case, the variation of the SRP may reflect the differences of the replication costs. However, both the $Vstock$ and the BAS display a different story. The average stock trading volume does not show any monotonicity across 20 portfolios and the relative bid-ask spreads are also very close across portfolios, suggesting that the cross-sectional differences of the realized SRP are not driven by the replication costs.

Next, I report market betas of each portfolio relative to the market skewness risk premium ($mSRP$) and the market variance risk premium ($mVRP$) to check whether portfolios capture different market risks proxied by the $mSRP$

[1] Bakshi et al. (2003) show theoretically that, within a power-utility economy in which returns are leptokurtic, the implied skew is greater in magnitude than the physical skew.

or $mVRP$. More exactly, I employ the monthly SRP data of each portfolio to estimate market betas by running the following regression:

$$SRP^{p}_{t,t+1} = \alpha + \beta \cdot MF_{t,t+1} + \epsilon_t$$

where $SRP^{p}_{t,t+1}$ is the monthly SRP (30-day maturity) of each of 20 portfolios, and $MF_{t,t+1}$ is the market factor, which is either $mSRP_{t,t+1}$ or $mVRP_{t,t+1}$. And the $mSRP_{t,t+1}$ ($mVRP_{t,t+1}$) is calculated by using the options written on the S&P 500 index. The results are reported in the eighth (ninth) column of Table 2.1. As in the case of the average realized SRP, the betas on $mSRP$ also show a big cross-sectional variation, ranging from 0.20 for P1 to 0.46 for P20. Similar pattern is also found to the $mVRP$ betas, ranging from 0.29 for P1 to 1.06 for P20. The different betas reflect that 20 SRP level-sorted portfolios are exposed to different market risks proxied by $mSRP$ and $mVRP$. In this case, it is reasonable to conjecture that both the $mSRP$ and the $mVRP$ have some explanatory power to the cross-sectional variation of skewness risk premia. What is interesting here is that the $mVRP$ betas are usually larger than the $mSRP$ betas, which implies that the $mVRP$ factor, if it is relevant, may be more powerful than the $mSRP$ factor in explaining the cross-sectional variation of skewness risk premia.

[Figure 2.1 about here]

Instead of using full sample to estimate market betas, I plot in Figure 2.1 the rolling $mSRP$ betas and $mVRP$ betas for several representative SRP level-sorted portfolios. The rolling estimation employs 60 monthly observations. As expected, I observe that the rolling $mSRP$ betas (top panel) show a similar pattern with the rolling $mVRP$ betas (bottom panel) across portfolios in the Figure 2.1. More importantly, both $mSRP$ betas and $mVRP$ betas exhibit a very different time series behavior across portfolios – portfolio 1 has relatively low rolling betas while portfolio 20 has relatively high rolling beta values, which is consistent with the pattern of the full sample betas in the Table 2.1. In addition, it is worth mentioning that the rolling betas before 2008 are more volatile than that afterwards.

The existing literature mainly studies the skewness risk premium on the market index, and we know little about the skewness risk premium for individual equities. To the best of my knowledge, this is the first paper to study skewness risk premium at the individual level by infering it from a synthetical skew swap directly. Hence, I report the differences of the SRP for each of these 20 SRP level-sorted portfolios relative to the market skewness risk premium $mSRP$ in the second last column of Table 2.1 ($Dif - mSRP$). Correspondingly, the t-statistics are also reported for these differences in the last column of Table 2.1. It is clear to see that most portfolio's SRP is significantly different from $mSRP$, which in turn supports the necessity of examining the behavior of skewness risk premium at the individual level.

In order to provide a clear picture of the differences of skewness risk premia across portfolios, I report in Table 2.2 the results of pair-wise comparison of skewness risk premia for several representative portfolios. Overall, the results in Table 2.2 indicate that skewness risk premia across portfolios are indeed significantly different with each other. For example, the SRP of portfolio 1 is significantly lower (more negative) than that of other four portfolios. Similarly, portfolio 5 earns a significantly smaller SRP than portfolios 10, 15 and 20. Although the SRP of portfolio 10 is smaller than that of portfolio 15, the difference is insignificant. Finally, I also observe that portfolio 15 yields a significantly lower SRP compared to the portfolio 20. More importantly, the overall significant differences of SRP across portfolios further justify the following analysis of the cross-sectional variation of SRP.

[Table 2.2 about here]

Before discussing the determinants of the cross-sectional variation of SRP, I report in Table 2.3 the pair-wise correlation coefficients between skewness risk premia of 20 SRP level-sorted portfolios. In addition, Table 2.3 also shows the correlation coefficients of the SRP between each of the 20 SRP level-sorted portfolios and the market index (second last column). As in the case of $mSRP$ betas reported in Table 2.1, the correlations of each of 20 portfolios with the market skewness risk premium ($mSRP$) display an increase trend, going from 0.05 for P1 to 0.33 for P20. This is not surprising especially when you consider that these portfolios are constructed by letting portfolio 1 contains securities with the lowest average skewness risk premium and letting portfolio 20 includes securities with the highest average skewness risk premium. Besides, the correlation coefficients are significant in most of cases. Both the monotonically increased $mSRP$ betas in Table 2.1 and the almost monotonically increased correlations with $mSRP$ in Table 2.3 imply that the $mSRP$ seems to include some explanatory power to the cross-sectional differences of skewness risk premia payoffs across portfolios. In the next section, I will test formally the determinants of the cross-sectional variation of skewness risk premia.

[Table 2.3 about here]

2.5 Cross-Sectional Variation of Skewness Risk Premia

2.5.1 Testing Framework

To investigate the factors that potentially drive the cross-sectional variation of skewness risk premia (SRP) across portfolios, I test all the stochastic discount factor (SDF) specifications in Section 2.2 with the two-pass cross-sectional regression approach of Fama and MacBeth (1973) by following the literature such as Chang et al. (2013), González-Urteaga and Rubio (2016), among others. In particular, I specify the form of factor models to make the above discussed SDF specifications can be adapted to the Fama-MacBeth two-pass regression framework. I test the competing asset pricing models (SDF specifications) which determine the cross-sectional differences of skewness risk premium payoffs by estimating risk loadings (β) of each 20 portfolios on the potential risk factors in the first step, inferring risk premium (λ) related to each of the risk loadings and checking whether they are significant or not in the second pass. Specifically, I test the following linear specifications using the 20 SRP level-sorted portfolios. For all specifications, λ_0 is the zero-beta rate and λ_k is the risk premia associated with the k-th risk factor that drives the cross-sectional variation of skew swap payoffs for the 20 portfolios. The superscript p indicates portfolio p, and $p = 1,\ 2,\ \dots, 20$.

I first consider models based on the consumption-based SDF specifications:

Model 1. Power utility with aggregate consumption:

$$E(SRP^p_{t,t+1}) = \lambda_0 + \lambda_c \cdot \beta^p_c \tag{2.22}$$

Model 2. Recursive preferences with the unobservable continuation value proxied by either the market excess return (Rm) or the return on total wealth (Rw):

$$E(SRP^p_{t,t+1}) = \lambda_0 + \lambda_c \cdot \beta^p_c + \lambda_{R_m} \cdot \beta^p_m \tag{2.23}$$

$$E(SRP^p_{t,t+1}) = \lambda_0 + \lambda_c \cdot \beta^p_c + \lambda_{R_w} \cdot \beta^p_w \tag{2.24}$$

Next, I turn to the models derived from the factor-based SDF specifications:

Model 3. The model with higher-order moments of equity returns according to Bakshi et al. (2003) and Bakshi and Madan (2006):

$$E(SRP^p_{t,t+1}) = \lambda_0 + \lambda_{R_m} \cdot \beta^p_m + \lambda_{R^2_m} \cdot \beta^p_{m^2} \tag{2.25}$$

$$E(SRP^p_{t,t+1}) = \lambda_0 + \lambda_{R_m} \cdot \beta^p_m + \lambda_{IV} \cdot \beta^p_{IV} + \lambda_{ISKEW} \cdot \beta^p_{ISKEW} + \lambda_{KS} \cdot \beta^p_{KS} \tag{2.26}$$

Model 4. The CAPM-type model with the market skewness risk premium ($mSRP$) as the only factor and a two-factor model with the $mSRP$ and the market excess return (R_m) as factors:

$$E(SRP^p_{t,t+1}) = \lambda_0 + \lambda_{mSRP} \cdot \beta^p_{mSRP} \quad (2.27)$$

$$E(SRP^p_{t,t+1}) = \lambda_0 + \lambda_{R_m} \cdot \beta^p_m + \lambda_{mSRP} \cdot \beta^p_{mSRP} \quad (2.28)$$

Model 5. A two-factor model with the $mSRP$ and the market variance risk premium ($mVRP$) as factors:

$$E(SRP^p_{t,t+1}) = \lambda_0 + \lambda_{mSRP} \cdot \beta^p_{mSRP} + \lambda_{mVRP} \cdot \beta^p_{mVRP} \quad (2.29)$$

Model 6. A three-factor model with the Rm, the $mSRP$, and the $mVRP$ as factors:

$$E(SRP^p_{t,t+1}) = \lambda_0 + \lambda_{R_m} \cdot \beta^p_m + \lambda_{mSRP} \cdot \beta^p_{mSRP} + \lambda_{mVRP} \cdot \beta^p_{mVRP} \quad (2.30)$$

For all the above specifications (equations (2.22) - (2.30)), β responds to the factor loading estimated in the first step of the Fama and MacBeth (1973) cross-sectional regression while λ denotes the estimated risk premium related to the risk captured by β. In addition to the aforementioned six models, the Fama and French (1993) three factors, Fama and French (2015) five factors, the momentum factor proposed by Carhart (1997), and the two macroeconomic factors Ted_t and Def_t are also tested in the empirical implementations.[1] The pair-wise correlation coefficients between these variables are reported in the Appendix 2.9.

To unify the testing framework, all the above specifications can be represented as $E(SRP) = X\lambda$, where $X = [1_N, \beta]$ and $\lambda = [\lambda_0, \lambda'_K]'$ is a vector consisting of the zero-beta rate λ_0, and the risk premia on the K factors λ_K. Therefore, the pricing errors of the N portfolios can be represented by

$$e = E(SRP) - X\lambda \quad (2.31)$$

In order to pick out the best one from competing models, I follow Kan et al. (2013) to compute the cross-sectional R^2 to measure the goodness of fit. Specifically, the R^2 is given by

$$R^2 = 1 - \frac{Q}{Q_0} \quad (2.32)$$

[1]When considering the Fama and French (1993) three factors, the Fama and French (2015) five factors, and the Carhart (1997) momentum factor, I test different combinations of these factors. However, the results indicate that only the market factor is significantly priced in some cases, all other factors are helpless in explaining the cross-sectional variation of skewness risk premia.

where

$$Q = e'V^{-1}e, \qquad Q_0 = e_0'V^{-1}e_0$$
$$e = [I_N - X(X'V^{-1}X)^{-1}X'V^{-1}]E(SRP)$$
$$e_0 = [I_N - 1_N(1_N'V^{-1}1_N)^{-1}1_N'V^{-1}]E(SRP)$$

e represents the pricing errors of the N assets, and e_0 represents the deviations of mean returns from their cross-sectional average. V is the variance-covariance matrix of the portfolio skewness risk premia. Based on the above definition, $0 \leq R^2 \leq 1$ and it is a decreasing function of the aggregate pricing errors Q, and therefore, R^2 is a well-defined and reasonable measure of the goodness of fit. In practice, I report R^2 for average returns instead of the average of monthly R^2 values.

In order to test whether a model has some explanatory power for pricing assets cross-sectionally, i.e., to test the null hypothesis $R^2 = 0$, Kan et al. (2013) construct a test statistic and prove that it can be represented by a summation of independent chi-square random variables asymptotically. Specifically, R^2 satisfies the following asymptotic distribution

$$T \cdot R^2 \overset{A}{\sim} \sum_{j=1}^{K} \frac{\xi_j}{Q_0} \chi_j \tag{2.33}$$

where T is the number of observations used to calculate R^2, $\chi_j' s$ are independent χ_1^2 random variables and $\xi_j' s$ are the K nonzero eigenvalues of

$$[\beta' V^{-1}\beta - \beta' V^{-1} 1_N (1_N' V^{-1} 1_N)^{-1} 1_N' V^{-1}\beta] V(\hat{\lambda}_1) \tag{2.34}$$

where $V(\hat{\lambda}_1)$ is the variance of the estimated coefficients and it is adjusted by errors-in-variables (EIV) and misspecification of the model. As pointed out by Kan et al. (2013), the estimated coefficients $\hat{\lambda}$ has the following asymptotic distribution after considering potential model misspecification

$$\sqrt{T}(\hat{\lambda} - \lambda) \overset{A}{\sim} N(0_{K+1}, V(\hat{\lambda})) \tag{2.35}$$

where

$$V(\hat{\lambda}) = \sum_{j=\infty}^{\infty} E[h_t h_{t+j}']$$

with

$$h_t = \underbrace{(\lambda_t - \lambda)}_{variance\ without\ any\ adjustment} - \underbrace{(\hat{\phi}_t - \hat{\phi})\hat{\omega}_t}_{EIV\ adjustment} + \underbrace{Hz_t}_{misspecification\ adjustment}$$

and

$$\phi_t = [\lambda_{0,t}, (\lambda_{1,t} - f_t)']', \quad \phi = [\lambda_0, (\lambda_1 - E(f))']'$$
$$u_t = e'V^{-1}(SRP_t - E(SRP)), \quad \omega_t = \lambda_1'\Omega^{-1}(f_t - E(f))$$
$$H = (X'V^{-1}X)^{-1}, \quad z_t = [0, u_t(f_t - E(f))'\Omega^{-1}]'$$

where f_t represents the factors and Ω is the variance-covariance matrix of the factors.[1]

2.5.2 Cross-Sectional Empirical Results

In Table 2.4, I report the estimated coefficients using the Fama and MacBeth (1973) two-pass cross-sectional regression method for alternative asset pricing models. Panel A contains the regression results relaying on the consumption-based factors, while Panel B presents the regression results concerning the factor-based models. In all cases, I adapt the testing framework to the Fama and MacBeth (1973) two-pass cross-sectional approach by estimating the rolling betas using 60 months observations. Specifically, I start with a rolling window of 59 months of past data plus the month in which I perform the cross-sectional regression for all 20 portfolios. In this case, for each month t, I get a beta which is estimated with 60 observations.[2] Finally, I obtain monthly estimators of the price of the risk specified in the first stage. I then take the average of these monthly estimators to yield the final estimated coefficients. What's more, I report in the parentheses below the estimators the p-values associated with the traditional Fama-MacBeth standard errors, and in the brackets the p-values related to the errors-in-variables (EIV) and model-misspecification adjusted standard errors.

[Table 2.4 about here]

Table 2.4 shows that the factor-based models (Panel B) in general have better performance than the consumption-based models (Panel A) in explaining the cross-sectional variation of skewness risk premia (SRP). Regarding the consumption-based models in Panel A, we cannot reject the model in which the representative agent is equipped with recursive preferences and earns the total

[1] The Newey and West (1987) method is employed to obtain a consistent estimate of the $V(\hat{\lambda})$.

[2] Different from the original Fama and MacBeth (1973) approach, some studies however use the full sample data to get first-stage beta estimates (e.g., Kan et al. (2013)). As an alternative robustness check, I also estimate the full-sample betas in the first stage and use these betas in the second stage regression, and the results by using these fixed-term betas are qualitatively similar with the results using rolling beta estimates. The main results using fixed-term betas are reported in the Subsection 2.6.3.

wealth return since the R^2 is significantly different from zero with p-value equals to 0.020. However, the risk premia estimates associated with the aggregate consumption growth are insignificant in all three cases. Therefore, it is reasonable to argue that the consumption risk is helpless in explaining the cross-sectional variation of SRP in this paper.

Panel B of Table 2.4 displays the regression results by implementing the factor-based SDF specifications. Compared to the consumption-based SDF specifications in Panel A, the R^2 for the asset pricing specifications in Panel B are usually larger and significant, suggesting that factor-based models explain the cross section of SRP much more accurately. The market skewness risk premium factor ($mSRP$) is significantly priced in the cross section of SRP only when we ignore the potential model misspecification. It becomes helpless in explaining the cross-sectional variation of SRP after controlling for the potential model misspecification because the coefficient on the $mSRP$ is insignificant when the p-value is calculated with the model misspecification adjusted standard error. In addition, I observe that, except the last two models, the asset pricing specification is not statistically rejected under 5% confidence level as long as the market variance risk premium factor ($mVRP$) is added into the model. More importantly, among these selected models, only the $mVRP$ is significantly priced across different specifications especially after controlling for the potential model misspecification. For example, in the single factor specification with the $mVRP$ as the unique independent factor (second row of Panel B), the coefficient on the $mVRP$ is 0.405, which is significantly different from zero with model misspecification adjusted p-value at 0.000. Similarly, this coefficient becomes 0.416 (p-value: 0.000) and 0.415 (p-value: 0.001) in the three factor (fourth row of Panel B) and five factor (ninth row of Panel B), respectively. What's more, the estimated coefficients associated with $mVRP$ are very consistent across models, which is around 0.4 on a monthly basis.

In addition to the $mVRP$, the market excess return (Rm) seems also to be priced to the cross-sectional variation of SRP in some cases. For instance, in the fourth, fifth, and ninth rows of Panel B, the estimated coefficients related to Rm are significant even though it only marginally different from zero in the fifth row (two-factor model) of Panel B. Besides, Panel B also shows (seventh and eighth rows) that the higher moments of the distribution of market log returns are not priced in the cross section of SRP although they have been shown useful to explain the skewness risk premium at the market level (see Bakshi et al. (2003)). Moreover, the results in the last two rows of Panel B display that the two macro factors – default risk premium (Def) and the spread between the three-month LIBOR and the three-month U.S. Treasury-bill rate (Ted) – are also helpless to explain the cross-sectional variation of SRP across portfolios even though they are crucial factors to the cross-sectional variation of variance risk premia (see González-Urteaga and Rubio (2016)).

In summary, I find that the market variance risk premium ($mVRP$) and the market excess return (Rm) are the key factors to explain the cross-sectional differences of SRP across portfolios. This is espeicially the case for the $mVRP$ even if I allow for the potential model misspecification. The single $mVRP$ factor explains significantly 36.1% of the variation of SRP cross sectionally. Moreover, it generates statistically significant premia of 0.405 on a monthly basis for the $mVRP$ factor. Loosely speaking, the positive estimated coefficient for the $mVRP$ factor indicates that the skewness risk is tightly related to the variance risk, which echoes the findings of Kozhan et al. (2013). What's more, it also means that the higher the market variance risk premium beta is, the higher the average payoff expected from skew swaps in the cross section. Recall that the $mVRP$ betas are positive for all portfolios in the Table 2.1, and hence the positive premium associated with the $mVRP$ factor is consistent with the general idea that return and risk are positively correlated. However, in the meanwhile, it is worth pointing out that the selected $mVRP$ and Rm factors are not enough to fully explain the cross-sectional variation of SRP across portfolios given the test of $R^2 = 1$ is significantly rejected (fifth row of Panel B).[1]

2.5.3 Double-Sort Analysis

The above analysis shows that the explanatory power of the $mSRP$ factor to the cross-sectional variation of SRP is shaded by the $mVRP$ factor. Besides, the $mVRP$ factor has also been shown to be the key factor to explain the cross-sectional variation of variance risk premia (e.g., González-Urteaga and Rubio (2016)). Given skewness risk premium and variance risk premium are highly correlated with each other (see Eraker (2008), Kozhan et al. (2013), among others), it is reasonable to doubt that the successful of the $mVRP$ in this paper may be because the 20 SRP level-sorted portfolios have very different variance risk premia (VRP).[2] To deal with this concern, I conduct a conditional double-sort exercise to control for the effects of the variance risk premium.[3] Specifically, in each month, I first sort securities into decile portfolios based on their VRP, and then I sort securities in each VRP decile portfolio into decile portfolios by their SRP. The conditional double-sort technique generates 100 portfolios. Then I construct the final 10 SRP level-sorted portfolios as follows: portfolio 1 contains all

[1]Although the two-factor model with the market variance risk premium and the market excess return as the factors is not enough to fully explain the cross-sectional variation of skewness risk premia across portfolios, it still generates a substantial $R^2 = 0.361$, which is significantly different from zero.

[2]The correlation between the market skewness risk premium $mSRP$ and the market variance risk premium $mVRP$ is about 0.65 in this paper.

[3]I calculate the average monthly variance risk premia (VRP) for the 20 SRP level-sorted portfolios, and find that there does not exists clearly trend of VRP across portfolios.

securities in the lowest SRP decile across all VRP-based decile portfolios while portfolio 10 includes all securities in the highest SRP decile in each VRP-based decile portfolios. The sorting procedure is updated monthly. The formed portfolios are held over the next month and their equal-weighted SRP are calculated for all decile portfolios. Then I conduct the Fama and MacBeth (1973) two-pass cross-sectional analysis on these newly generated portfolios. The main results are reported in Table 2.5.[1]

[Table 2.5 about here]

Overall, the results in Table 2.5 are consistent with the results in the Table 2.4. For the conditional double-sorted SRP portfolios, the market variance risk premium ($mVRP$) is still the key factor explaining the cross-sectional variation of SRP across portfolios. Moreover, the single $mVRP$ factor generates a significant large R^2 which equals to 0.59. In addition, the estimated risk premia to the $mVRP$ factor is 0.41, which is also very close to the value in the Table 2.4. To summarize, the results in Table 2.5 support the previous finding that the $mVRP$ is significantly priced in the cross section of skewness risk premium payoffs.

To provide a visually picture of how does the selected factor model performance in explaining the cross-sectional variation of SRP, Figure 2.2 displays the average realized monthly SRP values against the average fitted SRP values for two representative models. The left panel shows the performance of the univariate model in which the $mVRP$ is the unique factor, while the right panel presents the results from a two-factor model with the $mVRP$ and the Rm as factors. It is clearly to see that there is not big improvement in fitting data by adding the market excess return Rm into the model, which is consistent with the previous finding that the Rm factor is marginally significant in pricing the SRP in the cross section. Moreover, the single $mVRP$ factor presents a good fit across portfolios. However, the difficulty of the two models in explaining the two extreme portfolios, P1 and P20, must be recognized. Both models are generating a relatively smaller payoff for P1 and P20 in magnitude than the actual data, making them hard to obtain a more precise linear fit to the actual data.[2]

[1] As a robustness check, I also conduct an exercise by sorting all securities into two groups instead of 10 portfolios in the first step based on their variance risk premia (VRP) in each month. After that, I sort securities in each VRP-based group into decile portfolios in the second step. Then these portfolios are held over the next month, and their equal-weighted skewness risk premia are calculated. I do cross-sectional analyses of the portfolios in the two VRP-based groups separately and the results are presented in the Subsection 2.6.4.

[2] To eliminate the concern that the main results are driven by the two extreme portfolios, P1 and P20, I also conduct the cross-sectional analysis only for P2 to P19 portfolios as a robustness check. The results show that the single factor model with the $mVRP$ as the factor generates a R^2 at 0.362, which is significantly different from zero. What's more, the estimated coefficient to the $mVRP$ is 0.393, which is not only significantly different from zero but also comparable with the value in Table 2.4, that is 0.405.

[Figure 2.2 about here]

2.6 Robustness Analysis

The above analysis shows that the two-factor model with the Rm and the $mVRP$ as factors is successful in explaining the cross-sectional differences of the skewness risk premia across portfolios. In this section, I consider several robustness checks of the aforementioned main empirical results, including the sensitivity to the sample periods, the sensitivity to the methodology used to compute the legs of the swap contracts, the sensitivity to the first-step beta risk estimates, and the sensitivity to the way to conduct double-sort analysis.

2.6.1 Subsample Analysis

The sample used in this paper covers the period from January 1996 to August 2015. Such a period is characterized by a sharp stock market decline during the financial crisis starting from 2007, and then recovery. What's more, Figure 2.1 also shows that the rolling market variance risk premium ($mVRP$) betas present very different behavior before and after financial crisis. To verify that the main results are not driven by the peculiar circumstances in the sample period, I repeat the cross-sectional variation analysis on two equal-length non-overlapping subperiods: 1996-2005 and 2006-2015. The main results are reported in Table 2.6.

[Table 2.6 about here]

The results in Table 2.6 indicate that the above full sample results are insensitive to business cycles. In particular, the estimated coefficients for both factors are still significant in both periods except the coefficient for the Rm factor in the first subperiod. Moreover, the two-factor asset pricing specification explains 15.3% and 25.0% of the cross-sectional variation of SRP in two subperiods, respectively. Both R^2 are statistically significantly different from zero even after controlling for the potential model misspecification.

2.6.2 Interpolation and Extrapolation Method

Although Kozhan et al. (2013) point out that the way they used to compute implied moments are standard (see also Bollerslev et al. (2009)), some papers like Jiang and Tian (2005) and Carr and Wu (2009) however use the interpolation and extrapolation procedures to calculate implied volatilities and other moments. To check whether the results are sensitive to the methodology used for computing implied moments, I employ the implied moments computed by this alterative interpolation-extrapolation approach to do a robustness check.

In particular, I follow the procedures in Jiang and Tian (2005) to infer implied moments using equations (2.14) and (2.15). To calcualte these implied moments, the option prices with continuous strikes are needed in principle. However, in reality, options are traded with only limited strikes. To solve this issue, I follow the literature and apply the curve-fitting method to the Black and Scholes implied volatilities instead of applying the method to option prices.[1] Specifically, I first transform the prices of listed calls (puts) with a fixed maturity using the Black and Scholes model into implied volatilities, and then a smooth function is fitted to these implied volatilities by applying cubic splines.[2] Based on the fitted function, I extract the implied volatilities corresponding to 50 strikes, and then the Black and Scholes model is used one more time to obtain option prices which are corresponding to these 50 strikes.[3] When the range of available strikes is not sufficiently large, I follow Jiang and Tian (2005), Chang et al. (2013), among others, and use the endpoint implied volatility to extrapolate option prices for those options whose prices outside the range between the minimum and the maximum available strikes. Finally, I apply the above equations (2.14) - (2.21) to calculate the model-free implied moments and related premiums with these extracted option prices and strikes.

Based on these newly constructed variables, I repeat the above two-pass cross-sectional regression analysis, and the main results are reported in Table 2.7. I observe that the results in Table 2.7 are very close to the results in Table 2.4. On average, factor-based specifications perform much better than consumption-based specifications in explaining the cross-sectional variation of skewness risk premia. The two-factor asset pricing specification with the $mVRP$ and the Rm as factors is not statistically rejected. What's more, it generates statistically significant risk premia of 0.405 and -0.042 for the $mVRP$ and the Rm, respectively. The R^2 of the two-factor model is equal to 0.336 with the model-misspecification adjusted p-value equals to 0.051. These estimates are pretty close to their counterparts in Table 2.4. In total, we can safely conclude that the two-factor asset pricing

[1] In order to apply Black and Scholes, I need the continuously compounded dividend rate. For the index, I employ the daily data of dividend yield from OptionMetrics, and for individual asset, I infer the continuously compounded dividend rate by combining the forward price with the spot price used for the forward calculation, and then I take the average of the inferred dividend yield for the whole period as the final dividend yield for each asset.

[2] The purpose of using Black and Scholes model is to obtain a one-to-one mapping between option prices and implied volatilities. As pointed out by Jiang and Tian (2005), the curve-fitting procedure does not assume that the Black and Scholes model is correct for pricing options.

[3] As claimed by Jiang and Tian (2005), the discretization errors are negligible when we have more than 20 strikes, and I choose 50 strikes instead of the usual choice of 100 strikes in order to reduce the burden of computation.

specification with the $mVRP$ and the Rm as risk factors is successful in explaining the cross-sectional variation of skewness risk premia.

[Table 2.7 about here]

2.6.3 Fixed Beta Analysis

To apply the two-pass cross-sectional regression approach of Fama and MacBeth (1973) to test the models described in Subsection 2.5.1, I follow the original Fama and MacBeth (1973) and estimate the rolling betas in the first step. Some studies however argue that it has become more customary in recent decades to use the full-sample to estimate beta risks (see Kan et al. (2013)), and therefore, as an alternative robustness check, I also conduct the cross-sectional analysis by using fixed betas which are estimated by employing the full sample in the first stage. Results are reported in Table 2.8.

[Table 2.8 about here]

Overall, results based on the fixed beta estimates (Table 2.8) are qualitatively similar with the results relaying on rolling beta estimates (Table 2.4). It is clearly to see that, in Table 2.8, the consumption risk is still helpless in explaining the cross-sectional variation of skewness risk premia (SRP) while the market variance risk premium ($mVRP$) continuous to be significantly priced in the cross section of SRP. Besides, different from the rolling beta case in Table 2.4, the market skewness risk premium ($mSRP$) seems also to be priced to the cross section of SRP under the fixed beta setup. Moreover, the market excess return (Rm) factor becomes insignificant in explaining the cross section of SRP once the fixed beta is used.

2.6.4 Dichotomy Double-Sort Analysis

Different from the conditional double-sort analysis in the subsection 2.5.3 where I sort securities into 10 portfolios based on their variance risk premia (VRP) in the first step, I here sort securities into two groups based on their VRP in the first step. Specifically, the Low-VRP group contains all the securities with VRP values smaller than the median in each month while the High-VRP group includes all the securities with VRP values larger than the median in each month. Then, for each VRP-based group, I construct 10 skewness risk premium (SRP) level-sorted portfolios by sorting all securities into decile portfolios based on their SRP. In particular, portfolio 1 includes the securities with the lowest SRP levels, while portfolio 10 contains the highest ones. The ranking procedure is updated monthly. Then these decile portfolios are held over the next month and their equal-weighted skewness risk premia are calculated . After that, I employ these double-sorted portfolios to do the Fama and MacBeth (1973) two-pass cross-sectional analysis. The main results are reported in Table 2.9.

[Table 2.9 about here]

Overall, the results in Table 2.9 are consistent with the results in Table 2.4. In both VRP level-sorted groups, the asset pricing specification with the $mVRP$ and the Rm as factors is not statistically rejected. In particular, for the Low-VRP group, this two-factor model has a R^2 of 0.68 with model-misspecification adjusted p-value equals to 0.000, and for the High-VRP group, the same model generates a R^2 at 0.62, and the corresponding p-value is 0.020. In addition, the estimated risk premia to the $mVRP$ factor are 0.398 and 0.569 for Low and High-VRP groups, respectively, which is also comparable with the 0.400 in Table 2.4. What is more interesting is that the R^2 of the above two-factor model for the conditional double-sorted portfolios is larger than that for the SRP level-sorted portfolios in Table 2.4, but the R^2 for the Low-VRP group doesn't very different from the R^2 for the High-VRP group. In summary, the results in Table 2.9 support the previous finding that both the $mVRP$ and the Rm are priced in the cross section of skewness risk premium payoffs.

2.7 Why Does the Market Variance Risk Premium Matter?

The above analyses show that both the market variance risk premium ($mVRP$) factor and the market factor (Rm) are significantly priced cross sectionally with respect to skewness risk premia (SRP).[1] Then, it is natural to ask why these factors, especially the $mVRP$ factor matters in explaining the cross-sectional variation of SRP. In this section, I attempt to provide an economic interpretation of the above main empirical findings, particularly focusing on why the $mVRP$ is a priced factor in the cross section of SRP.

The different $mVRP$ betas across portfolios in the Table 2.1 and the Figure 2.1 seem to imply that the success of the $mVRP$ factor in explaining the cross-sectional variation of SRP can be explained by the very different behavior that 20 SRP level-sorted portfolios have with respect to the $mVRP$. If this hypothesis is true, then we should expect that the $mVRP$ betas for 20 SRP level-sorted portfolios exhibit a monotonic trend. I report in Table 2.10 the estimated $mVRP$

[1] The findings in this paper that the market variance risk premium and the market excess return are pricing factors is consistent with the theoretical and empirical work in Bollerslev et al. (2009) and Bali and Zhou (2016).

betas from full sample for 20 SRP level-sorted portfolios under different model specifications.

[Table 2.10 about here]

The first column of Table 2.10 is the same as the first column of the Table 2.1, showing the average realized SRP values for 20 SRP level-sorted portfolios. Moving to the $mVRP$ betas (columns 3, 5, 7, and 9), it is clearly to see that the $mVRP$ betas are positive for most of portfolios and increase almost monotonically from portfolio 1 (P1) to portfolio 20 (P20) under different asset pricing model specifications. For example, under the single-factor setup (third column), the $mVRP$ beta increases from 0.294 for P1 to 1.055 for P20, while under five-factor setup (ninth column), the $mVRP$ beta ranges from -0.474 to 1.335. Overall, the increasing trend of the $mVRP$ betas across portfolios suggests that different portfolios are taking different risks proxied by the $mVRP$, which further explains why the $mVRP$ factor is priced in the cross section of the skewness risk premium payoffs.[1]

Given the main results in Table 2.4 are using the rolling betas, while the $mVRP$ betas reported in Table 2.10 are estimated using the full sample, so it is necessary to estimate the rolling $mVRP$ betas for 20 SRP level-sorted portfolios under different model specifications. In particular, I first use the rolling 60 months window to estimate the $mVRP$ betas for each of the 20 portfolios. Then I report the time series average of the rolling betas for all portfolios in Figure 2.3. It is obviously that the average rolling $mVRP$ betas show an increasing trend from P1 to P20 under different asset pricing model specifications. In summary, both the results in Table 2.10 and Figure 2.3 show that the success of the $mVRP$ factor in the cross-sectional variation of skewness risk premia seems to be explained by the very different behavior that 20 SRP level-sorted portfolios have with respect to the risk proxied by the $mVRP$.[2] It is worth mentioning that the $mVRP$ factor has also been shown to play a key role in explaining the cross-sectional variation of stock returns as well as the cross-sectional variation of volatility risk premia (see Han and Zhou (2012), Feunou et al. (2017), and González-Urteaga and Rubio (2016)). Overall, the empirical findings seem to suggest that the market variance

[1] The market variance risk premium is often interpreted as a proxy of economic uncertainty or macroeconomic risk (e.g., Bali and Zhou (2016), Bollerslev et al. (2009), Drechsler and Yaron (2011)), so the higher the exposure of an asset to the market variance risk premium, the more risk is taken by that asset.

[2] The different exposures of 20 SRP level-sorted portfolios with respect to the $mVRP$ mean that different portfolios are bearing different market (uncertainty) risk. In fact, both the variance risk premium and the skewness risk premium are often interpreted as the compensation for the downside risk (e.g., Bollerslev and Todorov (2011), Kelly and Jiang (2014), Gabaix (2012), Drechsler and Yaron (2011), Bates (2000), Schneider and Trojani (2015)).

risk premium is a common risk in the market, which deserves further exploration in the future.

[Figure 2.3 about here]

2.8 Conclusion

The existing literature mainly focuses on estimating skewness risk premium of the market index, showing that the market skewness risk premium on average is negative, and it has rich economic implications to the equity returns. Moreover, a large and still growing body of literature show that skewness risk at the individual level also plays a crucial role both in asset pricing and in portfolio management. Given this evidence, however, surprisingly little is known about the skewness risk premium for individual equities. To the best of my knowledge, this paper is the first one to empirically analyze the feature of skewness risk premia on individual stocks. I first estimate the skewness risk premium for each stock from a synthetic skew swap, and then investigate the cross-sectional variation of the monthly skewness risk premia for a set of 20 portfolios.

In particular, I find that the skewness risk premia exhibit a considerably large dispersion across stocks. Then, I form 20 portfolios in each month based on the estimated skewness risk premia on individual equities in the prior month and then calculate the equal-weighted skewness risk premium for each formed portfolio. After that, I apply the Fama and MacBeth (1973) two-pass cross-sectional approach to analyze the determinants of the cross-sectional variation of skewness risk premia across portfolios. Empirical tests indicate that the beta risks related to the market variance risk premium and the market excess return have statistically significant risk premia, suggesting that the market variance risk premium and the market excess return are key factors that help explain the cross-sectional differences of the average skewness risk premium payoffs across portfolios. This is especially the case for the market variance risk premium factor, which is statistically significantly priced in the cross section with respect to skewness risk premia even if I allow for potential model misspecifications. Finally, I attempt to explain why the market variance risk premium factor matters to the cross-sectional variation of the skewness risk premia by drawing insight from the general risk-return trade-off. I show that the skewness risk premium level-sorted portfolios capture different degrees of the risk proxied by the market variance risk premium. The success of the market variance risk premium factor in the cross-sectional variation of skewness risk premia seems to be explained by the very different behavior that these skewness risk premium level-sorted portfolios have with respect to the market variance risk premium. It is worth mentioning that the market variance risk premium factor has also been shown to be priced in the cross section of equity returns and the cross section of volatility risk premia. This study provides further evidence that it is also priced in the cross section of skewness risk premia, suggesting that the market variance risk premium may represent a kind of common risk in the market, which deserves further studies in the future.

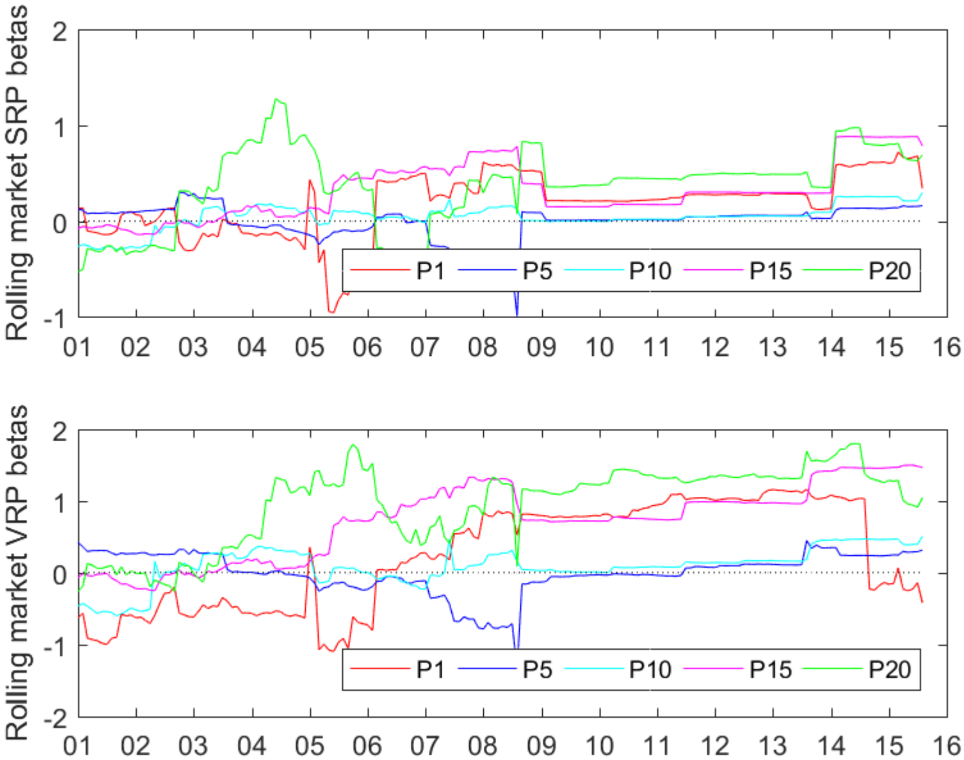


Figure 2.1: This figure displays the rolling market skewness risk premium betas and the market variance risk premium betas. The top panel shows the rolling market skewness risk premium betas while the bottom panel displays the rolling market variance risk premium betas for several representative skewness risk premium (SRP) level-sorted portfolios: P1, P5, P10, P15 and P20. For both panels, the rolling estimation employs 60-month observations. The data sample covers the period from January 1996 to August 2015.

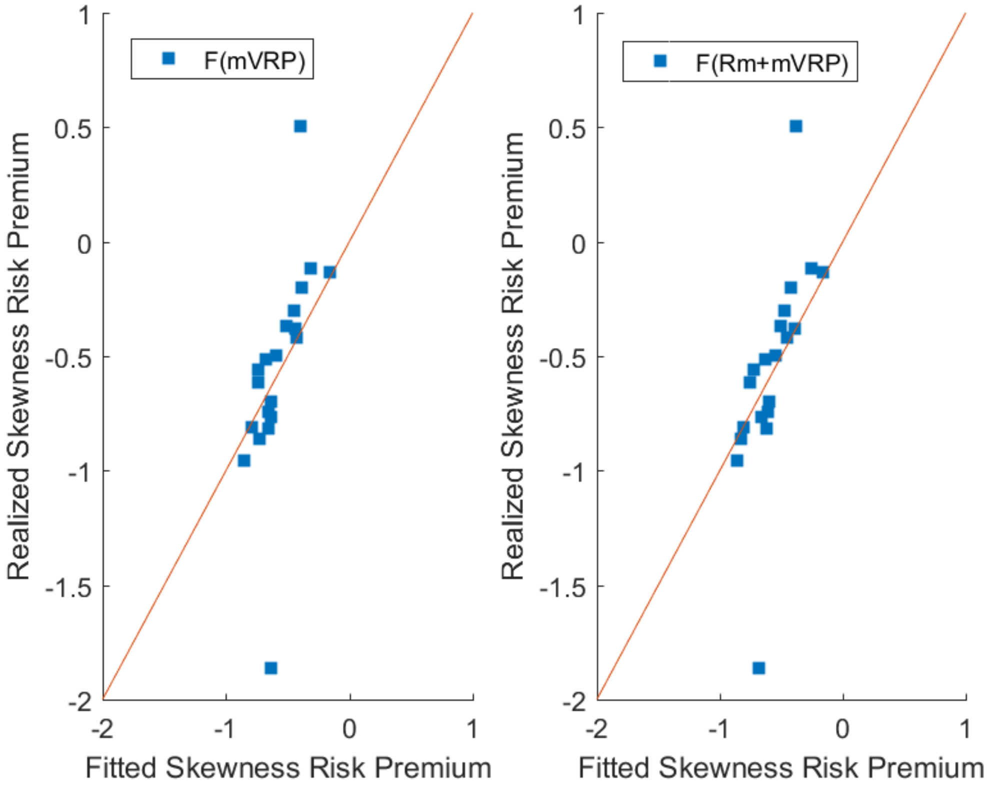


Figure 2.2: This figure displays the average realized monthly skewness risk premium (SRP) values against average fitted SRP values for 20 portfolios that are constructed based on the SRP in the previous month. The fitted SRP on the left panel is calculated from the selected single-factor ($mVRP$) model while the fitted SRP on the right panel is obtained from the selected two-factor ($mVRP + Rm$) asset pricing model. The data sample covers the period from January 1996 to August 2015.

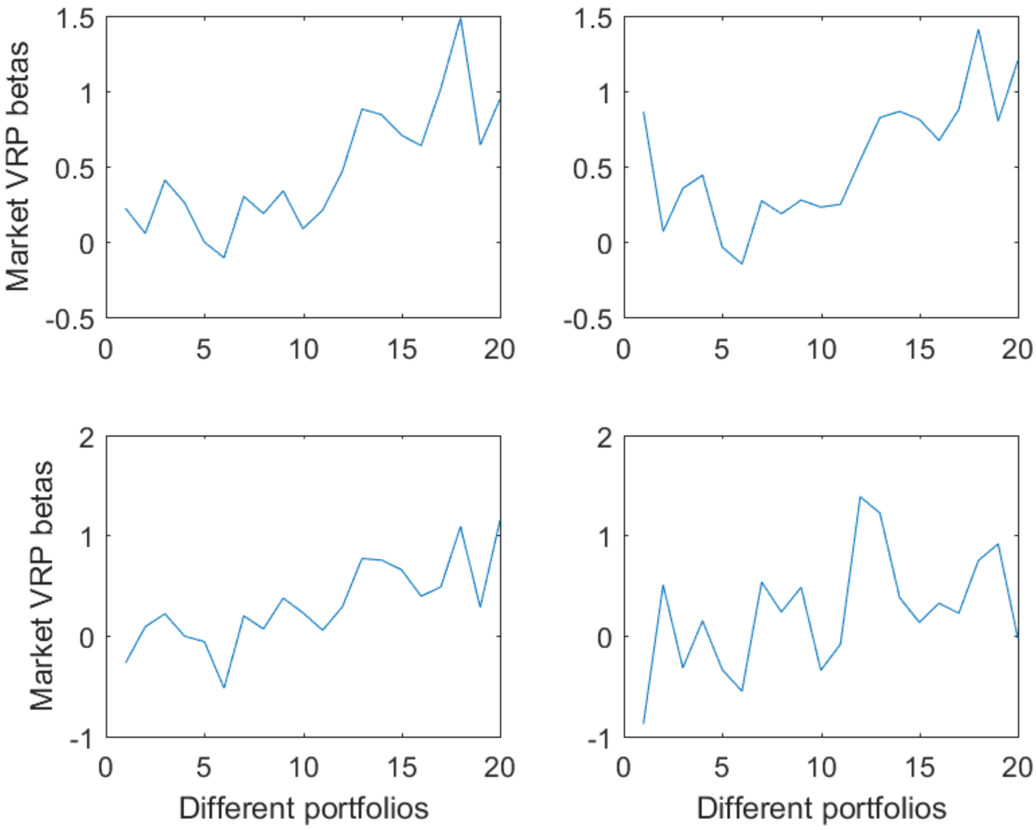


Figure 2.3: This figure displays the average rolling market variance risk premium ($mVRP$) betas under different model specifications for 20 portfolios that are constructed based on the estimated skewness risk premia (SRP) in the previous month. The top-left panel plots the average $mVRP$ betas estimated from the single factor model with $mVRP$ as the unique factor, while the top-right panel shows the average $mVRP$ betas which are estimated from a two-factor model with Rm and $mVRP$ as factors. In the bottom panel, the left part reports the $mVRP$ betas from a model with three factors ($Rm+mSRP+mVRP$), while the right part presents the $mVRP$ betas which are estimated from a five factor model ($Rm + mSRP + mVRP + Def + Ted$). The data sample covers the period from January 1996 to August 2015.

Table 2.1: Descriptive Statistics: SRP Level-Sorted Portfolios

	Mean	SD	Nobs	Median	Rstock	Vstock	BAS	mSRP-beta	mVRP-beta	Dif-mSRP	t
P1	-1.854	5.340	17.7	-0.945	0.012	$8.9e+07$	0.013	0.202	0.294	-1.380	-3.848^{***}
P2	-0.756	1.386	17.8	-0.863	0.007	$7.5e+07$	0.012	0.021	0.050	-0.282	-2.269^{**}
P3	-0.845	0.975	17.6	-0.894	0.010	$7.3e+07$	0.011	0.109	0.381	-0.370	-3.483^{***}
P4	-0.752	1.831	17.6	-0.901	0.010	$6.9e+07$	0.011	0.156	0.254	-0.278	-1.895^{*}
P5	-0.939	0.817	17.8	-0.885	0.010	$7.0e+07$	0.011	0.052	0.090	-0.465	-4.627^{***}
P6	-0.848	0.752	17.6	-0.822	0.010	$7.2e+07$	0.011	0.180	0.051	-0.373	-3.797^{***}
P7	-0.745	0.648	17.7	-0.803	0.009	$7.0e+07$	0.011	0.136	0.383	-0.270	-2.843^{***}
P8	-0.604	1.472	17.6	-0.775	0.009	$7.2e+07$	0.010	0.026	0.141	-0.130	-1.012
P9	-0.784	0.744	17.7	-0.799	0.012	$7.5e+07$	0.011	0.164	0.494	-0.309	-3.155^{***}
P10	-0.488	1.862	17.9	-0.667	0.009	$7.7e+07$	0.011	0.074	0.130	-0.013	-0.089
P11	-0.647	0.766	17.4	-0.655	0.011	$8.2e+07$	0.011	0.179	0.474	-0.172	-1.743^{*}
P12	-0.545	0.871	17.7	-0.617	0.010	$8.6e+07$	0.012	0.202	0.545	-0.071	-0.689
P13	-0.402	0.893	17.6	-0.538	0.014	$8.8e+07$	0.012	0.305	0.928	0.073	0.705
P14	-0.471	0.913	17.7	-0.601	0.012	$9.1e+07$	0.012	0.308	0.949	0.004	0.038
P15	-0.285	1.230	17.7	-0.477	0.011	$9.7e+07$	0.013	0.309	0.861	0.189	1.617
P16	-0.380	1.028	17.6	-0.496	0.013	$9.6e+07$	0.013	0.262	0.775	0.095	0.874
P17	-0.175	1.420	17.7	-0.385	0.007	$9.8e+07$	0.013	0.584	1.496	0.299	2.380^{**}
P18	-0.178	1.475	17.7	-0.438	0.009	$9.7e+07$	0.013	0.603	1.685	0.297	2.311^{**}
P19	-0.209	1.753	17.7	-0.362	0.007	$10.6e+07$	0.014	0.444	1.119	0.266	1.863^{*}
P20	0.504	3.604	17.6	-0.277	0.002	$11.5e+07$	0.015	0.455	1.055	0.978	3.913^{***}
SPX	-0.475	1.305	-	-0.669	-	-	0.004	-	-	-	-

This table presents descriptive statistics of the monthly (τ=30 day) realized skewness risk premia (SRP) for 20 SRP level-sorted portfolios and for the market, January 1996 to August 2015. The SRP is defined as the ratio of the realized skewness to the implied skewness minus 1, i.e., $SRP_{t,t+\tau} = RSKEW_{t,t+\tau}/ISKEW_{t,t+\tau} - 1$. Portfolio 1 contains the securities with the lowest SRP in the prior month while Portfolio 20 includes the highest ones. The portfolios are updated every month during the sample period. Columns under Mean, SD, Median report the sample average, standard deviation, and median of realized SRP, respectively. The column named Nobs reports the number of equities in each portfolio. 'Rstock' and 'Vstock' display the average monthly return and the average trading volume of stocks in each portfolio. 'BAS' is the relative bid-ask spread of each SRP level-sorted portfolio, which is the average of the bid-ask spread for all traded options on the underlying stocks that belong to a given portfolio. 'mSRP-beta' ('mVRP-beta') shows the portfolio betas, which are estimated from the ordinary least squares (OLS) regression on the market skewness risk premium $mSRP$ (market variance risk premium $mVRP$). The $mSRP$ ($mVRP$) is calculated by using the options written on the S&P 500 index. 'Dif-mSRP' presents the difference between each portfolio's SRP and the $mSRP$, and the next column reports the t-value of these differences. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 2.2: Pair-Wise Comparison

	P5	P10	P15	P20
P1	-0.915	-1.367	-1.569	-2.358
	(-2.597)	(-3.704)	(-4.389)	(-5.612)
	[0.010]	[0.000]	[0.000]	[0.000]
P5	-	-0.451	-0.654	-1.443
	-	(-3.403)	(-6.789)	(-5.986)
	-	[0.001]	[0.000]	[0.000]
P10	-	-	-0.202	-0.992
	-	-	(-1.391)	(-3.747)
	-	-	[0.166]	[0.000]
P15	-	-	-	-0.789
	-	-	-	(-3.177)
	-	-	-	[0.002]

This table shows the results of pair-wise comparison of skewness risk premia (SRP) for several representative portfolios: P1, P5, P10, P15, and P20. I report the pair-wise differences by using SRP values in each row minus SRP values in each column. The associated t-statistics and p-values are reported below the differences in the parentheses and brackets, respectively.

Table 2.3: Portfolio Correlations

	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16	P17	P18	P19	P20	mSRP	t
P1	0.002	0.066	0.009	-0.059	0.017	0.028	-0.031	-0.061	0.026	0.051	0.037	0.043	0.058	0.048	-0.018	0.076	0.010	0.028	0.019	0.049	0.754
P2	1.000	-0.043	-0.214	0.022	0.013	0.151	-0.059	-0.097	0.010	-0.080	0.015	-0.043	0.033	-0.028	0.112	0.057	0.010	-0.014	-0.113	0.020	0.299
P3	-	1.000	0.030	0.004	0.084	0.099	0.097	0.155	0.034	0.161	0.125	0.133	0.217	0.151	0.097	0.141	0.123	0.082	-0.128	0.146	2.250**
P4	-	-	1.000	0.017	-0.033	0.008	0.014	0.005	0.045	0.141	0.089	0.055	0.022	0.017	0.038	0.199	0.050	0.116	-0.004	0.112	1.714*
P5	-	-	-	1.000	0.048	0.018	-0.114	-0.030	0.098	0.055	0.020	0.148	0.043	0.106	0.124	0.186	0.143	0.026	0.085	0.082	1.263
P6	-	-	-	-	1.000	0.161	0.058	0.157	-0.135	0.299	0.167	0.111	0.179	0.186	-0.013	0.182	0.152	0.154	0.148	0.312	5.016***
P7	-	-	-	-	-	1.000	0.163	0.250	0.099	0.342	0.313	0.333	0.319	0.347	0.135	0.317	0.309	0.163	0.073	0.275	4.360***
P8	-	-	-	-	-	-	1.000	0.080	0.000	0.090	0.149	0.112	0.160	0.112	0.067	-0.028	-0.014	0.039	0.096	0.023	0.355
P9	-	-	-	-	-	-	-	1.000	-0.456	0.215	0.160	0.384	0.242	0.168	0.137	0.288	0.327	0.146	0.169	0.287	4.572***
P10	-	-	-	-	-	-	-	-	1.000	0.066	0.074	0.011	0.020	0.180	0.033	0.074	0.031	0.040	-0.036	0.052	0.792
P11	-	-	-	-	-	-	-	-	-	1.000	0.373	0.180	0.382	0.319	0.296	0.374	0.297	0.340	0.081	0.305	4.882***
P12	-	-	-	-	-	-	-	-	-	-	1.000	0.352	0.314	0.264	0.233	0.287	0.246	0.306	0.077	0.303	4.849***
P13	-	-	-	-	-	-	-	-	-	-	-	1.000	0.484	0.362	0.167	0.465	0.542	0.173	0.129	0.445	7.591***
P14	-	-	-	-	-	-	-	-	-	-	-	-	1.000	0.286	0.398	0.464	0.534	0.306	0.140	0.441	7.491***
P15	-	-	-	-	-	-	-	-	-	-	-	-	-	1.000	0.190	0.340	0.309	0.112	0.148	0.327	5.288***
P16	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1.000	0.345	0.349	0.410	0.087	0.332	5.379***
P17	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1.000	0.567	0.368	0.142	0.537	9.708***
P18	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1.000	0.320	0.128	0.533	9.626***
P19	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1.000	0.185	0.330	5.344***
P20	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1.000	0.165	2.548**

This table presents the pair-wise correlations of skewness risk premia (SRP) between different portfolios as well as the correlations of SRP between each of 20 portfolio and the market. The correlation coefficients are estimated by using monthly SRP of the full sample ranging from January of 1996 to August of 2015. The market skewness risk premium $mSRP$ is calculated by using the options written on the S&P 500 index. The column under 't' reports the t-statistics for the correlation coefficients between each of the 20 portfolios' SRP and the $mSRP$. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 2.4: SDF Specification Test – Two-Pass Cross-Sectional Regressions

	λ_0	λ_c	λ_{Rw}	λ_{Rm}	λ_{Rm^2}	λ_{IV}	λ_{ISKEW}	λ_{KS}	λ_{SMB}	λ_{HML}	λ_{mSRP}	λ_{mVRP}	λ_{Def}	λ_{Ted}	R^2
Panel A: Consumption-based SDF specifications															
Power with c	-0.765	0.042													0.000
	(0.000)	(0.146)													(0.890)
	[0.000]	[0.407]													[0.008]
$EZ + Rm$	-0.783	0.069		-0.036											0.240
	(0.000)	(0.020)		(0.000)											(0.070)
	[0.000]	[0.619]		[0.070]											[0.025]
$EZ + Rw$	-0.780	0.036	-0.002												0.413
	(0.000)	(0.201)	(0.000)												(0.020)
	[0.000]	[0.697]	[0.117]												[0.138]
Panel B: Factor-based SDF specificatioins															
$mSRP$	-0.784										0.410				0.157
	(0.000)										(0.001)				(0.136)
	[0.000]										[0.458]				[0.014]
$mVRP$	-0.789											0.405			0.361
	(0.000)											(0.000)			(0.000)
	[0.000]											[0.000]			[0.010]
$Rm + mSRP$	-0.800			-0.033							0.390				0.215
	(0.000)			(0.000)							(0.002)				(0.198)
	[0.000]			[0.198]							[0.495]				[0.011]
$Rm + mSRP + mVRP$	-0.804			-0.031							0.344	0.416			0.378
	(0.000)			(0.000)							(0.008)	(0.000)			(0.002)
	[0.000]			[0.028]							[0.414]	[0.000]			[0.002]
$Rm + mVRP$	-0.801			-0.032								0.408			0.361
	(0.000)			(0.000)								(0.000)			(0.001)
	[0.000]			[0.060]								[0.000]			[0.011]
$mSRP + mVRP$	-0.791										0.321	0.409			0.378
	(0.000)										(0.013)	(0.000)			(0.001)
	[0.000]										[0.443]	[0.000]			[0.009]
$Rm + Rm^2$	-0.788			-0.040	-0.000										0.289
	(0.000)			(0.000)	(0.356)										(0.098)
	[0.000]			[0.107]	[0.876]										[0.046]
$Rm + IV + ISKEW + KS$	-0.798			-0.035		-0.000	-0.156	0.010							0.253
	(0.000)			(0.000)		(0.429)	(0.062)	(0.506)							(0.256)
	[0.000]			[0.106]		[0.871]	[0.552]	[0.875]							[0.009]
$FF3 + mSRP + mVRP$	-0.793			-0.030					-0.013	0.000	0.286	0.415			0.518
	(0.000)			(0.000)					(0.000)	(0.927)	(0.029)	(0.000)			(0.019)
	[0.000]			[0.022]					[0.514]	[0.984]	[0.408]	[0.001]			[0.097]
$Rm + mSRP + mVRP$	-0.820			-0.031							0.271	0.392	0.000	-0.000	0.378
$+Def + Ted$	(0.000)			(0.000)							(0.030)	(0.000)	(0.808)	(0.885)	(0.167)
	[0.000]			[0.372]							[0.602]	[0.019]	[0.982]	[0.977]	[0.004]
$FF3 + mSRP + mVRP$	-0.818			-0.030					-0.011	0.001	0.290	0.413	0.001	0.000	0.541
$+Def + Ted$	(0.000)			(0.000)					(0.002)	(0.838)	(0.025)	(0.000)	(0.299)	(0.366)	(0.251)
	[0.001]			[0.352]					[0.835]	[0.972]	[0.582]	[0.145]	[0.944]	[0.889]	[0.250]

This table presents the parameters estimated from the two-pass cross-sectional Fama-MacBeth regressions for alternative asset pricing models. 20 skewness risk premium (SRP) level-sorted portfolios are used to test the proposed asset pricing models. These portfolios are formed as follows: equities are sorted into 20 portfolios based on their SRP in each month, then these portfolios are held over the next month and their equal-weighted SRP are calculated. The 60-month rolling window data is used to estimate betas in the first stage of the two-pass regression approach. The data sample covers the period from January 1996 to August 2015. R^2 is the cross-sectional R^2 calculated by using the method in Kan et al. (2013). Below the R^2, I report in the parentheses and brackets the p-values for testing $R^2 = 0$ and $R^2 = 1$, respectively. Except the last column, the numbers in the parentheses are the p-values corresponding to the Fama-MacBeth standard errors of the alternative parameter estimates, and the numbers in the brackets are p-values associated with the errors-in-variables (EIV) and model-misspecification adjusted standard errors. $FF3$ stands for Fama-French three factors.

Table 2.5: Two-Pass Cross-Sectional Regressions with Double-Sorted Portfolios

	λ_0	λ_c	λ_{Rw}	λ_{Rm}	λ_{Rm^2}	λ_{IV}	λ_{ISKEW}	λ_{KS}	λ_{SMB}	λ_{HML}	λ_{mSRP}	λ_{mVRP}	λ_{Def}	λ_{Ted}	R^2
Panel A: Consumption-based SDF specifications															
$Power\ with\ c$	-0.699	0.043													0.122
	(0.000)	(0.154)													(0.257)
	[0.000]	[0.797]													[0.015]
$EZ + Rm$	-0.727	0.098		-0.030											0.589
	(0.000)	(0.004)		(0.000)											(0.000)
	[0.000]	[0.424]		[0.136]											[0.188]
$EZ + Rw$	-0.737	0.029	-0.002												0.460
	(0.000)	(0.348)	(0.000)												(0.012)
	[0.000]	[0.840]	[0.140]												[0.036]
Panel B: Factor-based SDF specificatioins															
$mSRP$	-0.763										0.635				0.309
	(0.000)										(0.000)				(0.003)
	[0.000]										[0.072]				[0.013]
$mVRP$	-0.764											0.410			0.585
	(0.000)											(0.000)			(0.000)
	[0.000]											[0.000]			[0.048]
$Rm + mSRP$	-0.799			-0.023							0.566				0.601
	(0.000)			(0.000)							(0.000)				(0.000)
	[0.000]			[0.219]							[0.066]				[0.111]
$Rm + mSRP + mVRP$	-0.796			-0.017							0.395	0.385			0.749
	(0.000)			(0.004)							(0.014)	(0.000)			(0.000)
	[0.000]			[0.292]							[0.291]	[0.000]			[0.183]
$Rm + mVRP$	-0.793			-0.020								0.413			0.708
	(0.000)			(0.001)								(0.000)			(0.000)
	[0.000]			[0.337]								[0.000]			[0.145]
$mSRP + mVRP$	-0.778										0.428	0.371			0.646
	(0.000)										(0.007)	(0.000)			(0.000)
	[0.000]										[0.232]	[0.000]			[0.058]
$Rm + Rm^2$	-0.712			-0.039	-0.002										0.703
	(0.000)			(0.000)	(0.002)										(0.007)
	[0.000]			[0.011]	[0.412]										[0.255]
$Rm + IV + ISKEW + KS$	-0.706			-0.028		-0.001	-0.302	-0.039							0.743
	(0.000)			(0.000)		(0.277)	(0.025)	(0.132)							(0.057)
	[0.000]			[0.316]		[0.648]	[0.263]	[0.727]							[0.502]
$FF3 + mSRP + mVRP$	-0.827			-0.004					-0.017	-0.012	0.717	0.386			0.894
	(0.000)			(0.572)					(0.036)	(0.146)	(0.003)	(0.000)			(0.360)
	[0.002]			[0.962]					[0.709]	[0.934]	[0.704]	[0.524]			[0.946]
$Rm + mSRP + mVRP$	-0.798			-0.029							0.076	0.218	-0.003	-0.001	0.781
$+Def + Ted$	(0.000)			(0.001)							(0.673)	(0.002)	(0.091)	(0.108)	(0.054)
	[0.000]			[0.584]							[0.946]	[0.257]	[0.846]	[0.791]	[0.228]
$FF3 + mSRP + mVRP$	-0.773			-0.005					-0.025	-0.023	0.320	0.148	-0.007	-0.002	0.895
$+Def + Ted$	(0.000)			(0.648)					(0.023)	(0.042)	(0.248)	(0.108)	(0.013)	(0.126)	(0.650)
	[0.132]			[0.983]					[0.699]	[0.930]	[0.893]	[0.862]	[0.836]	[0.900]	[0.839]

This table presents the parameters estimated by employing the two-pass cross-sectional Fama-MacBeth regression approach to test a set of asset pricing models. Tested portfolios are formed based on the conditional double-sort approach. Equities are first sorted into 10 portfolios based on their estimated variance risk premia (VRP) and then in each VRP-based portfolio, equities are sorted into another 10 portfolios based on their estimated skewness risk premia (SRP). Then the final 10 SRP level-sorted portfolios are constructed as follows: portfolio 1 contains all securities in the lowest SRP decile across all VRP-based decile portfolios while portfolio 10 includes all securities in the highest SRP decile in each VRP-based decile portfolios. The sorting procedure is updated monthly. The formed portfolios are held over the next month and their equal-weighted SRP are calculated for all decile portfolios. R^2 is the cross-sectional R^2 calculated by using the method in Kan et al. (2013). Below the cross-sectional R^2, I report p-values in the parentheses and brackets for testing $R^2 = 0$ and $R^2 = 1$ respectively. Except the last column, the numbers in the parentheses are the p-values corresponding to the Fama-MacBeth standard errors of the alternative parameter estimates, and the numbers in the brackets are p-values associated with the errors-in-variables (EIV) and model-misspecification adjusted standard errors. FF3 stands for Fama-French three factors.

Table 2.6: Two-Pass Cross-Sectional Regressions – Subsamples

	λ_0	λ_{Rm}	λ_{mVRP}	R^2
Panel A: Sub-period: 1996-2005				
$mVRP$	-0.783		0.229	0.153
	(0.000)		(0.000)	(0.001)
	[0.000]		[0.005]	[0.071]
$Rm + mVRP$	-0.789	-0.019	0.238	0.153
	(0.000)	(0.027)	(0.000)	(0.081)
	[0.000]	[0.251]	[0.036]	[0.008]
Panel B: Sub-period: 2006-2015				
$mVRP$	-0.800		0.374	0.103
	(0.000)		(0.000)	(0.000)
	[0.000]		[0.000]	[0.012]
$Rm + mVRP$	-0.810	-0.036	0.368	0.250
	(0.000)	(0.000)	(0.000)	(0.000)
	[0.000]	[0.006]	[0.001]	[0.062]

This table presents the parameters estimated from the two-pass cross-sectional Fama-MacBeth regressions for the one-factor ($mVRP$) and two-factor (Rm and $mVRP$) asset pricing models with two equal-length non-overlapping subperiod samples. Panel A shows the results for sample period from January 1996 to December 2005, while Panel B displays the results for subperiod sample from January 2006 through August 2015. In each subperiod, 20 SRP level-sorted portfolios are used to test these asset pricing models. R^2 is the cross-sectional R^2 calculated by using the method in Kan et al. (2013). Below the R^2, I report the p-values in the parentheses and brackets for testing $R^2 = 0$ and $R^2 = 1$ respectively. Except the last column, the numbers in the parentheses are p-values corresponding to the Fama-MacBeth standard errors, and the numbers in the brackets are p-values associated with the errors-in-variables (EIV) and model-misspecification adjusted standard errors.

Table 2.7: Two-Pass Cross-Sectional Regressions – Alternative Calculated Implied Moments

	λ_0	λ_c	λ_{Rw}	λ_{Rm}	λ_{Rm^2}	λ_{IV}	λ_{ISKEW}	λ_{KS}	λ_{SMB}	λ_{HML}	λ_{mSRP}	λ_{mVRP}	λ_{Def}	λ_{Ted}	R^2
Panel A: Consumption-based SDF specifications															
Power with c	-0.773	-0.111													0.001
	(0.000)	(0.000)													(0.826)
	[0.000]	[0.113]													[0.006]
$EZ + Rm$	-0.782	-0.100		-0.035											0.270
	(0.000)	(0.000)		(0.000)											(0.032)
	[0.000]	[0.183]		[0.148]											[0.034]
$EZ + Rw$	-0.784	-0.104	-0.003												0.253
	(0.000)	(0.000)	(0.000)												(0.003)
	[0.000]	[0.045]	[0.000]												[0.011]
Panel B: Factor-based SDF specificatioins															
$mSRP$	-0.789										0.481				0.306
	(0.000)										(0.000)				(0.001)
	[0.000]										[0.030]				[0.014]
$mVRP$	-0.784											0.365			0.328
	(0.000)											(0.000)			(0.001)
	[0.000]											[0.007]			[0.007]
$Rm + mSRP$	-0.790			-0.032							0.472				0.333
	(0.000)			(0.000)							(0.000)				(0.025)
	[0.000]			[0.255]							[0.036]				[0.011]
$Rm + mSRP + mVRP$	-0.795			-0.029							0.430	0.373			0.338
	(0.000)			(0.000)							(0.000)	(0.000)			(0.061)
	[0.000]			[0.403]							[0.112]	[0.007]			[0.008]
$Rm + mVRP$	-0.795			-0.031								0.373			0.336
	(0.000)			(0.000)								(0.000)			(0.030)
	[0.000]			[0.330]								[0.005]			[0.005]
$mSRP + mVRP$	-0.794										0.421	0.367			0.328
	(0.000)										(0.000)	(0.000)			(0.006)
	[0.000]										[0.086]	[0.012]			[0.006]
$Rm + Rm^2$	-0.778			-0.039	-0.000										0.473
	(0.000)			(0.000)	(0.418)										(0.004)
	[0.000]			[0.109]	[0.845]										[0.111]
$Rm + IV + ISKEW + KS$	-0.778			-0.041		-0.000	-0.222	-0.056							0.476
	(0.000)			(0.000)		(0.505)	(0.004)	(0.036)							(0.014)
	[0.000]			[0.031]		[0.774]	[0.559]	[0.682]							[0.092]
$FF3 + mSRP + mVRP$	-0.809			-0.031					-0.008	-0.009	0.443	0.378			0.372
	(0.000)			(0.000)					(0.029)	(0.005)	(0.000)	(0.000)			(0.171)
	[0.000]			[0.508]					[0.746]	[0.519]	[0.110]	[0.001]			[0.005]
$Rm + mSRP + mVRP$	-0.789			-0.035							0.378	0.343	-0.001	-0.000	0.520
$+Def + Ted$	(0.000)			(0.000)							(0.000)	(0.000)	(0.244)	(0.952)	(0.015)
	[0.000]			[0.246]							[0.098]	[0.000]	[0.735]	[0.983]	[0.041]
$FF3 + mSRP + mVRP$	-0.798			-0.036					-0.005	-0.010	0.393	0.346	-0.001	0.001	0.585
$+Def + Ted$	(0.000)			(0.000)					(0.137)	(0.002)	(0.000)	(0.000)	(0.303)	(0.231)	(0.041)
	[0.000]			[0.311]					[0.806]	[0.368]	[0.093]	[0.000]	[0.777]	[0.645]	[0.141]

This table presents the parameters estimated from the two-pass cross-sectional Fama-MacBeth regressions. To calculate option-implied moments, the model-free method proposed by Jiang and Tian (2005) is used. 20 skewness risk premium (SRP) level-sorted portfolios are used to test a set of asset pricing models. These portfolios are formed as follows: equities are sorted into 20 portfolios based on their SRP in each month, then these portfolios are held over the next month and their equal-weighted SRP are calculated. The 60-month rolling window data is used to estimate betas in the first stage of the two-pass regression approach. The data sample covers the period from January 1996 to August 2015. R^2 is the cross-sectional R^2 calculated by using the method in Kan et al. (2013). Below the R^2, I report in the parentheses and brackets the p-values for testing $R^2 = 0$ and $R^2 = 1$, respectively. Except the last column, the numbers in the parentheses are the p-values corresponding to the Fama-MacBeth standard errors of the alternative parameter estimates, and the numbers in the brackets are p-values associated with the errors-in-variables (EIV) and model-misspecification adjusted standard errors. $FF3$ stands for Fama-French three factors.

Table 2.8: Two-Pass Cross-Sectional Regressions – Fixed Beta Estimates

	λ_0	λ_c	λ_{Rm}	λ_{Rm^2}	λ_{IV}	λ_{ISKEW}	λ_{KS}	λ_{SMB}	λ_{HML}	λ_{mSRP}	λ_{mVRP}	λ_{Def}	λ_{Ted}	R^2
Panel A: Consumption-based SDF specifications														
Power with c	-0.820	0.023												0.002
	(0.000)	(0.591)												(0.862)
	[0.000]	[0.862]												[0.004]
$EZ + Rm$	-0.836	0.030	-0.044											0.237
	(0.000)	(0.475)	(0.000)											(0.225)
	[0.000]	[0.739]	[0.162]											[0.012]
Panel B: Factor-based SDF specificatioins														
$mVRP$	-0.913										0.516			0.594
	(0.000)										(0.000)			(0.000)
	[0.000]										[0.000]			[0.073]
$Rm + mSRP + mVRP$	-0.925		-0.003							0.928	0.518			0.610
	(0.000)		(0.729)							(0.000)	(0.000)			(0.000)
	[0.000]		[0.883]							[0.019]	[0.000]			[0.060]
$Rm + mVRP$	-0.916		-0.002								0.516			0.605
	(0.000)		(0.780)								(0.000)			(0.000)
	[0.000]		[0.902]								[0.000]			[0.062]
$mSRP + mVRP$	-0.925									0.931	0.518			0.602
	(0.000)									(0.000)	(0.000)			(0.000)
	[0.000]									[0.023]	[0.000]			[0.052]
$Rm + Rm^2$	-0.849		-0.049	-0.001										0.284
	(0.000)		(0.000)	(0.081)										(0.082)
	[0.000]		[0.035]	[0.511]										[0.030]
$Rm + IV + ISKEW + KS$	-0.867		-0.054		0.000	-0.046	-0.086							0.328
	(0.000)		(0.000)		(0.852)	(0.730)	(0.004)							(0.301)
	[0.000]		[0.046]		[0.958]	[0.942]	[0.382]							[0.037]
$FF3 + mSRP + mVRP$	-0.935		-0.004					0.007	-0.003	1.044	0.512			0.627
	(0.000)		(0.699)					(0.240)	(0.747)	(0.000)	(0.000)			(0.002)
	[0.000]		[0.876]					[0.578]	[0.915]	[0.023]	[0.000]			[0.044]
$Rm + mSRP + mVRP$	-0.892		-0.006							0.864	0.494	-0.002	-0.000	0.631
$+Def + Ted$	(0.000)		(0.531)							(0.000)	(0.000)	(0.131)	(0.708)	(0.001)
	[0.000]		[0.796]							[0.027]	[0.000]	[0.442]	[0.881]	[0.051]

This table presents the parameters estimated from the two-pass cross-sectional Fama-MacBeth regressions. The data sample covers the period from January 1996 to August 2015. 20 skewness risk premium (SRP) level-sorted portfolios are used to test the proposed asset pricing models. These portfolios are formed as follows: equities are sorted into 20 portfolios based on their SRP in each month, then these portfolios are held over the next month and their equal-weighted SRP are calculated. The full sample is used to estimate betas in the first stage of the two-pass regression approach. R^2 is the cross-sectional R^2 calculated by using the method in Kan et al. (2013). Below the R^2, I report in the parentheses and brackets the p-values for testing $R^2 = 0$ and $R^2 = 1$, respectively. Except the last column, the numbers in the parentheses are the p-values corresponding to the Fama-MacBeth standard errors of the alternative parameter estimates, and the numbers in the brackets are p-values associated with the errors-in-variables (EIV) and model-misspecification adjusted standard errors. $FF3$ stands for Fama-French three factors.

Table 2.9: Two-Pass Cross-Sectional Regressions – Dichotomy Double-Sorted Portfolios

	λ_0	λ_c	λ_{Rm}	λ_{IV}	λ_{ISKEW}	λ_{KS}	λ_{mSRP}	λ_{mVRP}	λ_{Def}	λ_{Ted}	R^2
					Panel A: Low-VRP group						
$Power\ with\ c$	-0.708	-0.060									0.092
	(0.000)	(0.149)									(0.001)
	[0.000]	[0.116]									[0.008]
$EZ + Rm$	-0.729	-0.025	-0.031								0.438
	(0.000)	(0.567)	(0.000)								(0.110)
	[0.000]	[0.835]	[0.446]								[0.093]
$mVRP$	-0.745							0.415			0.643
	(0.000)							(0.000)			(0.000)
	[0.000]							[0.000]			[0.107]
$Rm + mSRP + mVRP$	-0.747		-0.020				0.409	0.435			0.691
	(0.000)		(0.047)				(0.263)	(0.000)			(0.019)
	[0.000]		[0.546]				[0.832]	[0.003]			[0.151]
$Rm + mVRP$	-0.741		-0.013					0.410			0.684
	(0.000)		(0.091)					(0.000)			(0.000)
	[0.000]		[0.606]					[0.000]			[0.189]
$mSRP + mVRP$	-0.743						0.343	0.436			0.644
	(0.000)						(0.183)	(0.000)			(0.024)
	[0.000]						[0.867]	[0.000]			[0.054]
$Rm + IV + ISKEW + KS$	-0.747		-0.031	0.001	-0.313	-0.038					0.671
	(0.000)		(0.000)	(0.370)	(0.007)	(0.114)					(0.162)
	[0.000]		[0.562]	[0.826]	[0.664]	[0.832]					[0.308]
$Rm + mSRP + mVRP$	-0.770		-0.016				0.417	0.487	-0.001	0.002	0.902
$+Def + Ted$	(0.000)		(0.156)				(0.317)	(0.000)	(0.450)	(0.045)	(0.029)
	[0.000]		[0.659]				[0.810]	[0.001]	[0.852]	[0.366]	[0.655]
					Panel B: High-VRP group						
$Power\ with\ c$	-0.729	-0.001									0.046
	(0.000)	(0.968)									(0.342)
	[0.000]	[0.990]									[0.009]
$EZ + Rm$	-0.746	0.049	-0.024								0.595
	(0.000)	(0.202)	(0.000)								(0.021)
	[0.000]	[0.676]	[0.402]								[0.165]
$mVRP$	-0.793							0.340			0.591
	(0.000)							(0.000)			(0.002)
	[0.000]							[0.023]			[0.066]
$Rm + mSRP + mVRP$	-0.804		-0.017				0.453	0.391			0.639
	(0.000)		(0.011)				(0.022)	(0.000)			(0.021)
	[0.000]		[0.673]				[0.552]	[0.006]			[0.083]
$Rm + mVRP$	-0.783		-0.016					0.365			0.620
	(0.000)		(0.015)					(0.000)			(0.016)
	[0.000]		[0.689]					[0.011]			[0.081]
$mSRP + mVRP$	-0.810						0.392	0.373			0.599
	(0.000)						(0.046)	(0.000)			(0.005)
	[0.000]						[0.603]	[0.002]			[0.056]
$Rm + IV + ISKEW + KS$	-0.780		-0.021	0.001	-0.256	-0.043					0.731
	(0.000)		(0.007)	(0.472)	(0.124)	(0.089)					(0.066)
	[0.000]		[0.478]	[0.710]	[0.262]	[0.824]					[0.165]
$Rm + mSRP + mVRP$	-0.841		-0.024				0.306	0.245	-0.003	-0.001	0.807
$+Def + Ted$	(0.000)		(0.005)				(0.152)	(0.003)	(0.085)	(0.112)	(0.231)
	[0.327]		[0.826]				[0.950]	[0.158]	[0.912]	[0.865]	[0.251]

This table presents the parameters estimated from the two-pass cross-sectional Fama-MacBeth regressions for alternative asset pricing models. The data sample covers the period from January 1996 to August 2015. Panel A reports the estimates from the portfolios contained in the low variance risk premia (Low-VRP) level group while Panel B presents the estimates based on the portfolios from the High-VRP level group. The Low-VRP group contains all the equities whose VRP values smaller than the median while the High-VRP group includes all the equities whose VRP values larger than the median. R^2 is the cross-sectional R^2 calculated by using the method in Kan et al. (2013). Below the R^2, I report in the parentheses and brackets the p-values for testing $R^2 = 0$ and $R^2 = 1$, respectively. Except the last column, the numbers in the parentheses are the p-values corresponding to the Fama-MacBeth standard errors of the alternative parameter estimates, and the numbers in the brackets are p-values associated with the errors-in-variables (EIV) and model-misspecification adjusted standard errors.

Table 2.10: Market Variance Risk Premium Betas for Different Specifications

	SRP	mVRP-beta(1)	t	mVRP-beta(2)	t	mVRP-beta(3)	t	mVRP-beta(4)	t
P1	-1.854	0.294	0.568	0.671	0.568	0.498	0.568	-0.474	0.568
P2	-0.756	0.050	0.409	0.038	0.409	0.019	0.409	0.656	0.409
P3	-0.845	0.381	3.343	0.363	3.343	0.373	3.343	0.595	3.343
P4	-0.752	0.254	2.122	0.399	2.122	0.238	2.122	-0.005	2.122
P5	-0.939	0.090	0.339	0.068	0.339	-0.004	0.339	-0.357	0.339
P6	-0.848	0.051	0.331	0.072	0.331	-0.350	0.331	-0.196	0.331
P7	-0.745	0.383	3.157	0.376	3.157	0.320	3.157	0.433	3.157
P8	-0.604	0.141	0.330	0.134	0.330	0.174	0.330	0.949	0.330
P9	-0.784	0.494	7.086	0.450	7.086	0.398	7.086	0.287	7.086
P10	-0.488	0.130	0.920	0.266	0.920	0.220	0.920	0.351	0.920
P11	-0.647	0.474	3.090	0.521	3.090	0.444	3.090	0.403	3.090
P12	-0.545	0.545	4.306	0.612	4.306	0.536	4.306	0.965	4.306
P13	-0.402	0.928	6.390	0.890	6.390	0.815	6.390	0.929	6.390
P14	-0.471	0.949	4.362	1.006	4.362	0.968	4.362	1.230	4.362
P15	-0.285	0.861	4.466	0.920	4.466	0.812	4.466	1.038	4.466
P16	-0.380	0.775	5.912	0.787	5.912	0.719	5.912	0.844	5.912
P17	-0.175	1.496	3.998	1.495	3.998	1.151	3.998	0.496	3.998
P18	-0.178	1.685	6.708	1.669	6.708	1.419	6.708	1.335	6.708
P19	-0.209	1.119	3.552	1.289	3.552	1.068	3.552	1.281	3.552
P20	0.504	1.055	2.765	1.120	2.765	0.786	2.765	0.266	2.765

This table presents the full sample market variance risk premia ($mVRP$) betas for 20 skewness risk premium (SRP) level-sorted portfolios under different model specifications. The column named 'SRP' reports the average monthly realized SRP values for 20 portfolios that are constructed based on the SRP values in the previous month. The column labeled 'mVRP beta(1)' reports the estimated $mVRP$ betas for the factor model with $mVRP$ as the unique factor. For 'mVRP beta(2)', 'mVRP beta(3)', and 'mVRP beta(4)', they display the estimated $mVRP$ betas for the model with two factors ($Rm+mVRP$), three factors ($Rm+mSRP+mVRP$), and five factors ($Rm + mSRP + mVRP + Def + Ted$), respectively. The columns named 't' report the t-statistics for the estimated $mVRP$ betas.

2.9 Appendix: Correlation Coefficients between State Variables

I report the correlation coefficients between the market skewness risk premium ($mSRP$) and several macroeconomic and financial indicators in Table A1. The data sample covers the period from January 1996 to August 2015. The correlation between the $mSRP$ and the market excess return (Rm) is negative and equals -0.144, which echoes the findings in the Table 2.4 where the estimated premium the market factor Rm is negative. The correlation between the $mSRP$ and the consumption growth is also negative, but is very small. The high positive correlation between the $mSRP$ and the $mVRP$ suggest that the market skew risk is tightly related with the market variance risk, which is consistent with findings in the existing literature (e.g., Kozhan et al. (2013) and Eraker (2008)). Besides, such positive relationship also provides the evidence to the explanation that both the market variance risk premium and the market skewness risk premium are regarded as the compensation for the downside or disaster risk (see Schneider and Trojani (2015), Doran et al. (2007), Bollerslev and Todorov (2011), Gabaix (2012), Kelly and Jiang (2014), among others).

Table A1: Correlation Coefficients between State Variables

	mVRP	C_g	Rm	SMB	HML	MoM	RMW	CMA	IV	ISKEW	KS	Def	Ted
mSRP	0.648	-0.043	-0.144	-0.066	0.168	-0.011	0.094	0.073	0.003	-0.055	-0.113	-0.067	0.035
mVRP	1.000	-0.166	-0.377	-0.074	0.128	0.090	0.198	0.117	0.138	0.121	0.142	0.144	0.181
C_g	-	1.000	0.197	0.165	-0.087	0.039	-0.195	-0.110	-0.346	-0.118	-0.213	-0.356	-0.231
Rm	-	-	1.000	0.223	-0.161	-0.275	-0.501	-0.359	-0.285	-0.120	-0.167	-0.111	-0.156
SMB	-	-	-	1.000	-0.324	0.104	-0.597	-0.127	-0.076	0.076	0.044	0.050	-0.032
HML	-	-	-	-	1.000	-0.197	0.480	0.641	-0.180	0.093	0.036	-0.098	-0.157
MoM	-	-	-	-	-	1.000	0.085	0.052	-0.053	-0.118	-0.063	-0.183	0.067
RMW	-	-	-	-	-	-	1.000	0.311	0.119	0.081	0.091	0.058	0.036
CMA	-	-	-	-	-	-	-	1.000	0.037	0.109	-0.027	0.037	-0.057
IV	-	-	-	-	-	-	-	-	1.000	0.494	0.293	0.673	0.557
ISKEW	-	-	-	-	-	-	-	-	-	1.000	0.653	0.383	0.368
KS	-	-	-	-	-	-	-	-	-	-	1.000	0.277	0.460
Def	-	-	-	-	-	-	-	-	-	-	-	1.000	0.249

This table reports the pair-wise correlation coefficients estimated for the full sample ranging from January 1996 to August 2015. $mSRP$ ($mVRP$) stands for the market skewness (variance) risk premium, calculated with the equation (2.20) (equation (2.21)) in the main text. C_g is the monthly growth rate of aggregate consumption per capita. Rm, SMB, HML, RMW, and CMA are Fama-French five factors. MoM is the momentum factor. IV, $ISKEW$, and KS stand for option-implied variance, skewness, and kurtosis, respectively. Def is the default risk premium, defined as the difference between Moody's yield on Baa corporate bonds and the 10-year Treasury Constant Maturity yield. Ted is the spread between the three-month LIBOR and the three-month U.S. Treasury-bill rate.

Chapter 3

Risk-Neutral Cumulants, Expected Risk Premia, and Future Stock Returns

3.1 Introduction

In a complete market, options are redundant assets in the sense that options can be perfectly replicated by trading underlying stocks and risk-free bond. However, under realistic assumptions of stochastic volatility, market illiquidity and so on, market incompleteness arises. In this case, option prices – which are inherently forward-looking – may therefore contain valuable information on future stock prices (see Breeden and Litzenberger (1978), Back (1993), Giamouridis and Skiadopoulos (2011), Christoffersen et al. (2013), Martin (2017), among others). To aggregate information in option prices, a large and still growing body of literature has focused on risk-neutral moments. However, there is no agreement on how to efficiently extract future returns-related information from a large set of risk-neutral moments. Some studies, for example, focus on short-term (one-month maturity) risk-neutral volatility, skewness or kurtosis (e.g., Xing et al. (2010), Bali and Murray (2013), Chang et al. (2013), and Stilger et al. (2016)), while others instead concentrate on the information contained in their long-term counterparts (e.g., Feunou et al. (2013), Vasquez (2017), and Borochin et al. (2018)). This study contributes to this strand of literature in two ways. Firstly, it exploits the information contained in the whole option price panels by building an empirical model – which is consistent with the extensively studied affine reduced-form option pricing framework (see Duffie et al. (2000), Feunou et al. (2013), and Feunou and Okou (2017)) – to connect option-implied cumulants at different orders and various maturities with expected risk premia via latent risk factors. Secondly, to estimate expected risk premia on individual stocks, it proposes a new easily implementable partial least squares-based estimation procedure that exclusively extracts future returns-relevant infromation contained in risk-neutral cumulants.

In particular, risk-neutral cumulants of different orders and various maturities are used to condense information contained in large option price panels,[1] and I then assume – inspired by the implication of the affine reduced-form option pricing models – that risk-neutral cumulants can be used to reveal underlying latent risk factors that are also related to expected risk premia under the assumption of factor structure.[2] To efficiently filter returns-related information from a large set of risk-neutral cumulants through latent factors, I propose a partial least squares-based estimation approach, which generates consistent estimates of the infeasible best forecasts for future stock returns. Based on the ex-ante filtered expected risk premia (FERP) of individual stocks, I further examine the relationship between the ex-ante FERP and future realized stocks' risk premia cross-sectionally. Empirically, I use daily option prices of all stocks that have been included in the S&P 500 index during the period from 1996 to 2017. Risk-neutral cumulants are calculated for each stock using the model-free methodology of Bakshi et al. (2003). Then, expected risk premia on individual stocks are filtered from a large set of risk-neutral cumulants by employing a new partial least squares-based algorithm.

To explore the predictability of FERP for future returns, I first implement portfolio sort analysis in ways similar to Fama and French (1996). Specifically, I sort all stocks into decile portfolios based on their ex-ante FERP in each month from January 1996 to December 2017. I then construct a high-minus-low spread portfolio that goes long the top decile portfolio and short the bottom decile portfolio. These portfolios are held over the next month and their equal-weighted risk premia and risk-adjusted alphas are computed. It is worth mentioning that portfolios that are constructed in each month only rely on the information up to that month, suggesting that the findings of the paper are not affected by look-ahead bias. I find significant evidence that the ex-ante FERP are positively related to future realized stocks' risk premia. In particular, both realized risk premia and risk-adjusted alphas (e.g., Fama and French (1993) three-factor adjusted alpha, Carhart (1997) momentum-factor adjusted alpha, Fama and French (2016) five-

[1] The cumulant-generating function is also suggested by Martin (2012) to characterize the properties of asset prices. Therefore, cumulants at different orders and various maturities, defined by taking the derivative of the log cumulant-generating function with respect to its argument, are enough to summarize the characteristics of the large option price panels.

[2] It is well established that the log cumulant-generating function can be represented as a linear function of underlying latent risk factors under the affine reduced-form option pricing framework with mild assumptions (see, e.g., Feunou et al. (2013) and Feunou and Okou (2017)). Moreover, I show that the filtered latent risk factors of this paper also characterize the option prices (see subsection 3.6.3).

factor adjusted alpha, Bollerslev et al. (2009) variance risk premium adjusted alpha, and Stambaugh and Yuan (2016) mispricing factor adjusted alpha) increase almost monotonically from portfolios 1 to 10 with respect to the ex-ante FERP. Moreover, the high-minus-low spread portfolio earns an average risk premium of 0.89% per month (t-stat: 3.20), and a Fama-French-Carhart four-factor adjusted alpha of 1.06% per month (t-stat: 3.75). In addition, the double-sort analyses show that the significantly positive relationship between the ex-ante FERP and future realized risk premia is robust to the widely studied short-term risk-neutral volatility, skewness, and kurtosis, and it is also not covered by the first principal component of the second-order cumulants, third-order cumulants, or fourth-order cumulants.

Besides portfolio-sort analysis, I further conduct Fama-MacBeth cross-sectional regressions to control for a large number of potential predictors. Specifically, I focus on three types of control variables: commonly studied variables such as market beta, market value, momentum, and book-to-market ratio; stock-related variables, including stock trading volume, short-term reversal, illiquidity, maximum and minimum daily return over the previous month, and the firm's default risk; and option-related variables that include option trading volume, option open interest, put-to-all options volume ratio, and option-implied short-term volatility, skewness, and kurtosis. Despite such extensive controls, the coefficient on the ex-ante FERP is always positive and statistically significant. For example, the coefficient on the FERP in the one (independent) variable model is 0.128 (t-stat: 3.17), and it ranges from 0.065 (t-stat: 2.08) to 0.090 (t-stat: 2.73) in multi-variable models. These results provide further support for the finding that the ex-ante expected risk premium filtered from a large set of risk-neutral cumulants is significantly positively related to future realized stocks' risk premia. Furthermore, these results also indicate that the newly proposed partial least squares-based approach is a promising estimation method to efficiently capture future returns-related information embedded in different option-implied cumulants.

I further investigate the source of the predictive power of the FERP and find that its predictability for future stock returns is consistent with the finding of Martin and Wagner (2018). Moreover, the FERP of the FERP-based high-minus-low spread portfolio is highly correlated with the expected market risk premium of Martin (2017) and with the equal-weighted expected stock's risk premium of Martin and Wagner (2018). In addition, I put forward a potential mechanism to explain the empirical findings by drawing insight from the sequential trade model of Easley et al. (1998). I assume without loss of generality that there are some informed investors in the market who perceive negative performance on some stocks due to private information. However, those negatively perceived stocks are too costly or too risky to sell short due to short-selling constraints, leading informed investors to resort to the option market. Johnson and So (2012) also show that short-sale constraints lead informed investors to trade options more frequently for negative signals than positive ones. In this way, the predictability of the FERP may reflect the trading activity of informed traders who choose to trade options before trading stocks due to short-selling constraints, leading option prices to carry information that leads stock price movements, which is consistent with the sequential trade model of Easley et al. (1998).[1]

To make the above conjectured mechanism valid, three conditions need to be satisfied. First, stocks characterized by higher short-selling constraints should be negatively perceived by informed investors, hence generating lower expected and future realized risk premia. Second, informed investors resorting to the option market due to short-selling constraints would imply that those highly short-sale constrained stocks should exhibit more active trading in options compared to stocks. Finally, the predictive power of the FERP should also be greater when options are more liquid relative to the underlying stocks, as predicted by Easley et al. (1998). To verify these hypotheses, I use three proxies for short-selling constraints: the relative short interest rate of Asquith et al. (2005), the estimated shorting fee of Boehme et al. (2006), and the idiosyncratic volatility under physical measure of Wurgler and Zhuravskaya (2002). The empirical tests confirm all the above hypotheses, indicating that the main findings of the paper can be potentially explained by informed trading driven by short-selling constraints.

3.1.1 Related Literature

This study pertains to the literature on the informational content of option prices. Considering that option prices are inherently forward-looking, they are extensively used in forecasting stock returns.[2] Some studies employ information embedded in option prices directly to infer future stock returns, while the others instead focus on the information contained in option trades.[3] Different from these studies, there is a large and still growing body of evidence indicating that

[1]Short-selling constraints in the stock market hinder the price mechanism from reflecting informed investors' beliefs, which is also in line with the argument of Miller (1977).

[2]Option-implied information is also widely used in asset allocation and risk management. See, for example, French et al. (1983), Kostakisa et al. (2011), Darolles et al. (2006), Jabbour et al. (2008), Buss and Vilkov (2009), Christoffersen (2011), Buss and Vilkov (2012), Giamouridis and Ntoula (2009), DeMiguel et al. (2013), Chang et al. (2011) and references therein.

[3]Manaster and Rendleman Jr (1982), Peterson and Tucker (1988), and Goncalves-Pinto et al. (2017) are several representatives who employ option-implied stock prices to infer future stock returns. To exploit the information embedded in option trades, see, for example, Chen et al. (2016), Bollen and Whaley (2004), Cremers et al. (2016), Hu (2014), Muravyev (2016), Pan and Poteshman (2006), Roll et al. (2010), Roll et al. (2014) and Ge et al. (2016).

expected stock returns tend to line up with option-implied moments such as volatility, skewness and kurtosis, and this paper belongs to this field.

Motivated by the well-documented negative correlation between changes in the implied volatility and changes in the underlying asset price, a number of papers have explored whether implied volatility indices can serve as leading indicators to forecast future stock returns. For example, Banerjee et al. (2007) find that the VIX forecasts future stock returns of NYSE stock portfolios formed on size, book-to-market ratio and beta. Ang et al. (2006) find that the VIX is a priced factor with a negative price of risk – stocks with higher sensitivities to the innovation in VIX exhibit lower future returns on average. DeLisle et al. (2010) find that the result in Ang et al. (2006) holds when volatility is rising but not when volatility is falling. Besides, the cross-sectional predictability of the option-implied idiosyncratic volatility is found by Diavatopoulos et al. (2008). An et al. (2014) argue that option-implied volatility incorporates incoming news about the underlying assets and find that increases in implied volatilities of at-the-money call options predict high subsequent stock returns, while increases in implied volatilities of put options predict low subsequent stock returns. Recently, Martin (2017) argues that the risk-neutral variance of the market provides a lower bound on the market equity premium under mild assumptions. Kadan and Tang (2017) extend the argument of Martin (2017) to individual stocks and show that a lower bound of the individual stock's expected return is roughly approximated by its risk-neutral volatility. Besides, Martin and Wagner (2018) go one step further and provide an explicit equation of the expected risk premium on individual stocks in terms of risk-neutral variance at the market and individual levels. Moreover, they show that the calculated expected risk premia have a big variation across stocks and they perform better than the traditional predictors in forecasting future stock returns.

In addition to risk-neutral variance/volatility, another strand of literature investigates if option-implied higher moments help explain the subsequent cross-section of stock returns. For example, Doran et al. (2006) focus on the implied skew and find that the implied volatility skew has strong predictive power for short-term market decline. This predictive power, however, is not always economically significant as argued by Doran et al. (2007). Rehman and Vilkov (2008) measure risk-neutral skewness with the model-free methodology of Bakshi et al. (2003) and find that risk-neutral skewness positively predicts the cross-section of stock returns, and such predictive power lasts up to five months. Diavatopoulos et al. (2012) document that changes in implied skewness and kurtosis prior to earnings announcements have strong predictive power for future stock and option returns. Besides, Chang et al. (2013) and Agarwal et al. (2009) show that option-implied higher moments of the S&P 500 index are also priced in the cross-section of stock returns. Although it is well-documented that option-implied higher moments are related to future stock returns, empirical studies sometimes obtain opposite findings on the relationship between risk-neutral higher moments and future stock returns. For instance, Conrad et al. (2013) find a negative relationship between option-implied skewness and the cross-section of future stock returns, while Rehman and Vilkov (2012) report a positive relationship, even though they both use the model-free skewness of Bakshi et al. (2003). One difference between these two studies is that the former uses average skewness over the last three months whereas the latter employs skewness measures computed only on the last available date of each month. Besides, consistent with the skewness preference theory, Bali and Murray (2013) also find a negative relationship between risk-neutral skewness and future equity returns. However, Stilger et al. (2016) and Bali et al. (2017) argue that the positive relationship between risk-neutral skewness and future stock returns can be explained by the demand-based option pricing model of Bollen and Whaley (2004) and Garleanu et al. (2008).

Existing literature provides strong evidence that expected stock returns are in line with option-implied moments, but it is worth pointing out that these studies usually either focus on a short-term or long-term risk-neutral moment of a specific order; hence they may miss parts of potential useful information contained in whole option price panels.[1] Moreover, risk-neutral moments may contain returns-unrelated information that makes them not ideal as variables used directly in performing portfolio sort analysis. This paper attempts to deal with these concerns.

The rest of the paper is organized as follows. Section 3.2 introduces the empirical model that builds a connection between information embedded in option price panels and expected risk premia. Section 3.3 describes the details of estimation methodology. In Section 3.4, I introduce the data and show how risk-neutral cumulants are calculated with option prices. Section 3.5 and Section 3.6 report the main findings and results of robustness checks, respectively. Then, in Section 3.7, I propose a potential explanation to support the findings of the paper. Section 3.8 concludes the paper.

[1] In fact, risks at different orders are not independent. For instance, Gormsen and Jensen (2017) show that higher-moment risks of the market derived from options move together, and therefore, if one of them is related to future stock return, it is reasonable to conjecture that the others are also relevant for future stock returns.

3.2 Theoretical Framework

3.2.1 Expected Return Specification

To connect expected return on individual stocks with option-implied information, I draw insight from the affine reduced-form option pricing framework. For any stock i, I assume there are L risk factors (or state variables), say $F_{i,t}$, which drive the return of stock i. Moreover, I assume that (1) the joint distribution of the one-period ahead excess log-return, $r_{i,t+1}$ and risk factors $F_{i,t+1}$ belongs to the family of affine jump-diffusion continuous-time (or discretized) models (see Duffie et al. (2000)); (2) the conditional stochastic discount factor is an exponential affine function of $r_{i,t+1}$ and $F_{i,t+1}$ (see Gourieroux and Monfort (2007)); and (3) the risk-free rate is an affine function of $F_{i,t+1}$.[1] Affine specifications generate the following general Laplace transform of excess returns under physical measure (P) (see Darolles et al. (2006))

$$E_t^P[exp(u \cdot r_{i,t+1} + v^T F_{i,t+1})] = exp(\beta_{r,0}^P(u,v) + \beta_{r,F}^P(u,v)^T F_{i,t}) \tag{3.1}$$

where $\beta_{r,0}^P(u,v)$ and $\beta_{r,F}^P(u,v)$ are functions of the argument u and the parameters of the underlying option pricing model. With equation (3.1) and assumptions of (1)-(3), Feunou et al. (2013) show that the cumulant-generating function of excess returns over an investment horizon τ, $r_{i,t+\tau}$, under the physical measure, P, is given by

$$E_t^P[exp(u \cdot r_{i,t+\tau})] = exp(\beta_{r,0}^P(u;\tau) + F_{i,t}^T \beta_{r,F}^P(u;\tau)) \tag{3.2}$$

Thereafter, by taking the first-order derivative of the log cumulant-generating function under the physical measure with respect to its argument u, the equity premium over an investment horizon τ is given by

$$\mu_{i,t}(\tau) = E_t^P[r_{i,t+\tau}] = b_0(\tau) + b_1(\tau)^T F_{i,t} \quad i = 1, 2, .., N \tag{3.3}$$

where $b_0(\tau)$ and $b_1(\tau)$ are also functions of the parameters of the underlying option pricing model.

However, this paper is not focused on building an option pricing model and hence it does not provide analytical expressions of $b_0(\tau)$ and $b_1(\tau)$. Nevertheless, equation (3.3) indicates that the expected return of any stock i is a linear function of the underlying risk factors $F_{i,t+1}$. Therefore, I assume in this paper that the one-period ahead expected excess log return of any stock i at time t has a factor

[1] Within the affine framework of Duffie et al. (2000) and Duffie et al. (2003), to understand the above three assumptions in the main text (subsection 3.2.1), see technical regularity conditions discussed on page 1351 in Duffie et al. (2000).

structure,[1] and it is given by

$$\mu_{i,t} = E_t[r_{i,t+1}] = B^T F_{i,t} \quad i = 1, 2, .., N \tag{3.4}$$

where B is an L-dimension column vector of factor loadings, and $F_{i,t}$ is an L-dimension vector of risk factors.[2] Under this framework, the realized risk premium on stock i at time $t+1$ can be written as

$$r_{i,t+1} = B^T F_{i,t} + \epsilon_{i,t+1} \quad i = 1, 2, .., N \tag{3.5}$$

where $\epsilon_{i,t+1},\ i = 1, 2, ..., N$ are unexpected returns, satisfying $E[\epsilon_{i,t+1}|I_t] = 0$, and I_t denotes the information set at time t. Besides, $\epsilon_{i,t+1}$ are allowed to be correlated across stocks. Unfortunately, for econometricians, the information in I_t is not fully accessible and both factors $F_{i,t}$ and factor loadings B in equation (3.4) are not directly observable. Hence, assessment of equation (3.4), i.e., infer expected risk premium μ_{it} remains challenging.

3.2.2 Latent Risk Factors and Risk-Neutral Cumulants

Although both B and $F_{i,t}$ in equation (3.4) are unobservable, the latent risk factors $F_{i,t}$ can be revealed from risk-neutral cumulants. Note that, similar to equation (3.2), the cumulant-generating function of excess returns over an investment horizon τ, $r_{i,t+\tau}$, under risk-neutral measure Q, is given by (see Feunou et al. (2013))

$$E_t^Q[exp(u \cdot r_{i,t+\tau})] = exp(\beta_{r,0}^Q(u;\tau) + F_{i,t}^T \beta_{r,F}^Q(u;\tau)) \tag{3.6}$$

where $\beta_{r,0}^Q(u;\tau)$ and $\beta_{r,F}^Q(u;\tau)$ are functions of the argument u and the parameters of the underlying option pricing model. They are solutions to ordinary differential equations (ODEs) based on the specified option pricing model. Again, this paper does not provide detailed expressions of the ODEs that are used to solve $\beta_{r,0}^Q(u;\tau)$ and $\beta_{r,F}^Q(u;\tau)$. I refer the interested readers to Duffie et al. (2000) and Duffie et al. (2003) for general expressions of these ODEs. Nevertheless, if we take the n-th order derivative of the log cumulant-generating function in equation (3.6) with respect to the argument u and then evaluate at $u = 0$, the risk-neutral n-th order

[1] Factor models are sufficiently general to subsume a wide range of models considered in the asset pricing literature, such as the CAPM model (e.g., Lintner (1965), Sharpe (1964) and Treynor (1961)), the Fama-French three and five-factor models (e.g., Fama and French (1993) and Fama and French (2016)), the momentum factor model (e.g., Carhart (1997)), and the APT (e.g., Ross (1976) and Roll and Ross (1980)).

[2] Adding a constant to equation (3.4) does not affect the following analysis because the estimation procedures only identify cross-sectionally demeaned expected risk premia.

cumulant ($CUM_{i,t}^{\tau}(n)$) of stock returns over any horizon τ can be represented as an affine function of $F_{i,t}$:[1]

$$CUM_{i,t}^{\tau}(n) = \alpha_{\tau,0} + \alpha_{\tau,F}^{T} F_{i,t} \tag{3.7}$$

where $CUM_{i,t}^{\tau}(n)$ stands for n-th order risk-neutral cumulant at time t with maturity τ for stock i, and $\alpha_{\tau,0}$ and $\alpha_{\tau,F}$ are again functions of the parameters of the underlying option pricing model. This paper attempts to exploit the linear relationship between risk-neutral cumulants and underlying risk factors without specifying an option pricing model, which is beyond this paper's scope (see Feunou et al. (2013) and Feunou and Okou (2017)).[2]

The equation (3.7) indicates that underlying latent risk factors $F_{i,t}$ can be revealed by risk-neutral cumulants at different orders with various maturities that can be calculated directly from option prices with the model-free method proposed by Bakshi et al. (2003). However, the model-free measured risk-neutral cumulants may differ from the true values because of measurement error, and therefore I assume that the model-free measured risk-neutral cumulant is linearly related to the latent risk factors with an error term:[3]

$$CUM_{i,t}^{\tau} = \Gamma_{l,\tau}^{T} F_{i,t} + \varepsilon_{i,t}^{\tau} \tag{3.8}$$

where $\Gamma_{l,\tau}, l = 1, 2, ..., L$ is L-dimension column vector that determines the sensitivity of observable option-implied cumulants $CUM_{i,t}^{\tau}$ to underlying risk factors $F_{i,t}$.[4] $\varepsilon_{i,t}^{\tau}$ are error terms which are allowed to correlated across stocks.[5]

To summarize, based on equations (3.4) and (3.8), this paper builds a connec-

[1] The use of cumulant-generating function to characterize the effect of higher-order cumulants on properties of asset prices is also suggested by Martin (2012) who consider the consumption-based asset pricing model with higher cumulants.

[2] In Appendix A2 of Feunou et al. (2013), they explain that the three above mentioned assumptions (subsection 3.2.1) are very general, which are satisfied by a wide array of discrete-time as well as continuous-time asset pricing models, such as the affine long-run risk models (see Bansal and Yaron (2004) and Eraker (2008) for example), and the continuous-time models of Gourieroux and Monfort (2007) and Christoffersen et al. (2009). For more details, interested readers can review Feunou et al. (2013).

[3] Notice that the above equation (3.8) applies to risk-neutral cumulants at different orders (e.g., second, third, and fourth order) with various maturities.

[4] The equation (3.8) ignores the constant term, which is consistent with the requirement of the partial least squares regression method (see Section 3.2 of Kelly and Pruitt (2015)). The details of the partial least squares-based method used in this paper is described in the Section 3.3.

[5] The idea that connecting latent factors $F_{i,t}$ (equivalent to factor loadings in the beta representation) with observable variables $CUM_{i,t}$ has also been explored by Kelly et al. (2018) who call the observable variables as instrumentals in their instrumented principal component analysis (IPCA) framework.

tion between unobservable expected risk premia $\mu_{i,t}$ and the observable option-implied cumulants $CUM_{i,t}^{\tau}$ through latent underlying risk factors $F_{i,t}$. In essence, equations (3.4) and (3.8) indicate that option-implied cumulants tend to align with stocks' expected returns, which is also suggested by various empirical studies (see Christoffersen et al. (2013) and references therein). More importantly, it is worth highlighting that the above model specification is consistent with the implication of the widely studied affine reduced-form option pricing models, which makes the findings of the paper not only meaningful from the perspective of investors, but also valuable for theoretical asset pricers in the sense that results of the paper may provide some insights about modeling option prices under the affine reduced-form framework. Subsection 3.6.3 provides a brief discussion of the option pricing performance of the filtered latent risk factors.

3.3 Estimation Methodology

Under the above specified framework, I describe in this section the details of the estimation approach used in the paper. In a short, I propose a partial least squares (PLS)-based method to extract returns-related latent factors from a large set of observed risk-neutral cumulants. This newly proposed estimation approach belongs to the partial least squares (PLS) algorithm family.[1] The PLS approach can be regarded as a dimension reduction technique, but compared to the classical principal component analysis (PCA) technique, PLS as pointed out by Kelly and Pruitt (2015) is a disciplined dimension reduction technique.[2] In this paper, the partial least squares technique condenses the cross-section of a large set of risk-neutral cumulants according to their covariances with the excess returns.

3.3.1 Estimation Procedures

To estimate expected risk premia under the framework described in Section 3.2, I propose a partial least squares (PLS)-based approach, which can be viewed as

[1]The partial least squares estimation approach was initially developed by Herman Wold in Wold (1975) and Wold (1982), which is widely used in computational chemistry and behavioral sciences (e.g., Frank and Friedman (1993), Wold et al. (2001) and Wang et al. (2010)), and recently, this approach has been introduced into finance by several authors. See, for example, Kelly and Pruitt (2013), Huang et al. (2015), Light et al. (2017) and Kelly and Pruitt (2015).

[2]PLS method identifies a factor with the best ability to predict the target variable even though this factor may not be the most important source of common variation in the predictors, which is the key difference as compared to the principal component analysis (PCA) because PCA is designed to extract one or few factors that concisely describe the variability of the predictors.

an implementation of the three-pass regression filter of Kelly and Pruitt (2015). But it is different from the three-pass regression filter approach in several aspects. First, the main purpose of this paper is to estimate expected risk premia on a variety of individual stocks at a given time from a large set of option-implied cumulants, whereas the three-pass regression filter focuses on finding the best forecast for a single variable from historical information-based predictors. In other words, the time dimension of the three-pass regression filter method in Kelly and Pruitt (2015) corresponds to the cross-section dimension of this paper, and the historical information based predictors in Kelly and Pruitt (2015) correspond to a large set of inherently forward-looking option-implied cumulants of this paper. Second, to estimate factor loadings and expected risk premia, this paper uses different option-implied cumulants while the three-pass regression filter uses the same set of predictors, indicating that this paper's estimation procedures allow to incorporate more information than that of Kelly and Pruitt (2015). In particular, the one-period lagged risk-neutral cumulants are used to estimate factor loadings first, and then the current period risk-neutral cumulants are employed to estimate expected risk premia.[1] Third, to make the risk-neutral cumulants at different orders with various maturities are measured in comparable units, they are demeaned and standardized in the cross-section, which is also required when using PLS-based regression method (see Section 3.2 of Kelly and Pruitt (2015)).[2]

In addition, this paper's estimation approach is also similar to the latent variable approach developed by Light et al. (2017). However, different from Light et al. (2017), I focus on extracting useful information on future stocks' returns from forward-looking option-implied cumulants through latent risk factors, whereas they concentrate on firm characteristics obtained from historical accounting data. Besides, this paper is interested in exploring the cross-section return predictability of the filtered expected risk premium and further provides an explanation to the empirical findings, while Light et al. (2017) spend time on comparing several different estimation approaches. In addition, Light et al. (2017) mainly focus on the single-factor model, whereas this paper – inspired by the affine option pricing framework – concentrates on the multi-factor model.

[1] The factor loadings of the expected risk premium on the latent risk factors in this paper are assumed to be fixed or there is not big change for two successive periods.

[2] Given I use demeaned risk-neutral cumulants when extracting latent risk factors, the estimation procedure only generates demeaned filtered expected risk premia. However, note that only the ranking of the filtered expected risk premia matters for cross-sectional analysis, and hence this paper's findings are not affected by using the demeaned filtered expected risk premia.

3.3.1.1 Details of Estimation

Under the above described framework, the main challenge – to estimate $\mu_{i,t}$ by filtering them out from the observable risk-neutral cumulants $CUM^{\tau}_{i,t}$ through latent risk factors – can be solved by implementing the following three steps:
Step 1: Estimate factor loadings

- At time t, for each maturity τ, regress standardized risk-neutral cumulants in the prior period $t-1$, $CUM^{\tau}_{i,t-1}, \tau = 1, 2, ..., S$, on the proxy variables $Z^{l}_{i,t}, l = 1, 2, ..., L$, in the cross-section. Then, save the estimated slopes as $\hat{\Gamma}^{\tau}_{t}$.

Step 2: Extract latent factors

- For each stock $i, i = 1, 2, ..., N$, put all maturities together, run regressions (in the maturity space) of standardized risk-neutral cumulants $CUM^{\tau}_{i,t-1}$ and $CUM^{\tau}_{i,t}$ on the $\hat{\Gamma}^{\tau}_{t}$ obtained in the Step 1, respectively.[1] Then, denote correspondingly the estimated slopes as $\hat{F}_{i,t-1}$ and $\hat{F}_{i,t}$.

Step 3: Compute filtered expected risk premia

- For all stocks, run cross-sectional regression of excess return $r_{i,t}$ on $\hat{F}_{i,t-1}, i = 1, 2, ..., N$, and denote the estimated slopes as $\hat{B}$. Based on the estimated factor loadings $\hat{B}$, the filtered expected risk premia of the next period are given by $\hat{\mu}_{i,t} = \hat{B}^{T}\hat{F}_{i,t}$.

The proxy variables $Z^{l}_{i,t}$ are chosen by adopting the suggestion of Kelly and Pruitt (2015) who propose an automatic proxy selection procedure (see Appendix A.6 and A.7 of their paper). In particular, each subsequent proxy is constructed as the forecasting error in the previous step, and the first proxy is set to be the target variable – excess return. Specifically, I construct the proxy variables $Z^{l}_{i,t}, l = 1, 2, ..., L$, as follows: I start with $Z^{1}_{i,t} = r_{i,t}$, and then I implement the above Steps 1-3 using $Z^{1}_{i,t}$ as the first proxy. A new proxy $Z^{l'}_{i,t}$ is calculated as $Z^{l'}_{i,t} = r_{i,t} - \hat{B}^{T}\hat{F}_{i,t-1}$. If $l' = L$, then the procedure is terminated. Otherwise, I repeat Steps 1-3 to form the next proxy. In the following empirical analysis, to be consistent with option pricing literature, this paper mainly focuses on the

[1] Note that I assume the factor loadings in the equation (3.8) is time-constant, but here the estimated factor loadings $\hat{\Gamma}^{\tau}_{t}$ is time-dependent, the way to understand this is that I assume that there is not big change of factor loadings for two successive periods.

scenario with $L = 2$, i.e., a two-factor model, but as a robustness check, I also consider the case of $L = 1$, and the main findings are robust.[1]

Generally, the above estimation procedures can be regarded as an implementation of the three-pass regression filter approach, suggesting that the consistency property of the three-pass regression filter estimates should also adapt to this paper's estimates. Kelly and Pruitt (2015) show that, for the single target variable, the three-pass regression filter is a consistent estimate of the infeasible best forecast of the target variable that uses all information available at that time (Theorem 1 of Kelly and Pruitt (2015)). Equivalently, I argue that the filtered expected risk premia in this paper are consistent estimates of the infeasible best forecasts of multiple future stocks' (demeaned) excess returns. Appendix 3.11 provides a proof of the consistency property of the estimates $\mu_{i,t}$ in this paper.

3.4 Data and Risk-Neutral Cumulants

3.4.1 Data

3.4.1.1 Option and Stock Data

The sample used in this paper combines different data sources and covers the period from January 1996 to December 2017. It is well known that options for individual stocks may be quite illiquid, and hence I limit my attention to a subset of stocks which are known to be actively traded and liquid.[2] Specifically, I focus on options written on stocks that were included in the S&P 500 index. In total, the sample contains 1004 stocks. Options on individual stocks are obtained from OptionMetrics (provided through Wharton Research Data Services (WRDS)). Volatility surface data are used to calculate risk neutral cumulants.

I download the volatility surface file, which contains the interpolated volatility surface for each security on each day. The implied volatility is computed using

[1] To build the connection between option-implied cumulants and expected risk premia, a crucial assumption in the paper is that risk-neutral cumulants are linear functions of latent underlying risk factors, which is drawn from widely studied affine reduced-form option pricing models. In terms of the affine option pricing framework, both two-factor and one-factor models are frequently used. See, for example, Bates (2000), Duffie et al. (2000), and Feunou et al. (2013) for the two-factor setup, and Heston (1993), Pan (2002), and Broadie et al. (2007) for the one-factor setup. Recently, several three-factor models were proposed by Gruber et al. (2015), Andersen et al. (2015a) and Andersen et al. (2015b), but in these models, such as the one by Andersen et al. (2015b), they show that only one factor contains relevant information about future stock returns. Therefore, to keep consistent with option pricing literature, this paper mainly focuses on $L = 2$ and $L = 1$.

[2] Hou et al. (2017) document that the alphas reported in a number of asset pricing studies become insignificant once small stocks are weighted less in the universe of test portfolios.

binomial trees that take into account the early exercise of individual stock options and the dividends expected to be paid over the life of the options. The volatility surface file encompasses information on standardized call and put options with maturities of 30, 61, 91, 122, 152, 182, 273, 365, 547, and 730 calendar days, at deltas of 0.20, 0.25, 0.30, ... , 0.75, and 0.80 (negative deltas for put options). Besides, a standardized option is included only if enough traded option prices are available on that date to accurately interpolate the required values. In addition to implied volatility, option premium and strikes are also provided for each security-maturity-moneyness combination. I end up with more than two and half million firm-day observations for all above mentioned horizons, covering a total of 1004 firms over 5537 trading days in my sample. I use out-of-the-money (OTM) options ($0 < |\Delta| < 0.5$) to compute risk-neutral cumulants with the model-free method of Bakshi et al. (2003). In particular, I use OTM options maturing in 30, 61, 91, 122, 152, 182, 273, 365, 547, and 730 days to calculate risk neutral cumulants for 1, 2, 3, 4, 5, 6, 9, 12, 18, and 24 months, respectively. A yield curve file is also downloaded from OptionMetrics, which is used to interpolate risk-free interest rates for the above mentioned maturities. In addition, I also collect option volume and option open interests data from Option Volume file in OptionMetrics, which are used to construct control variables considered in the cross-sectional regression analysis.

In addition to the options data, the daily and monthly stock returns, price, outstanding shares, and trading volumes are collected from the Center for Research in Security Prices (CRSP, provided through Wharton Research Data Services). Firms' accounting data are obtained from Compustat (provided through Wharton Research Data Services). These variables are used to calculate control variables that are considered in the cross-sectional Fama-MacBeth regressions. In addition, the Fama-French three and five factors (Fama and French (1993), Fama and French (2016)) and the Carhart momentum factor (Carhart (1997)) are downloaded from Kenneth French's webpage.[1] The variance risk premia factor, defined as the difference between the risk-neutral and objective expectations of realized variance, is obtained from Hao Zhou's webpage.[2] These commonly studied variables are used to calculate risk-adjusted risk premia.

3.4.1.2 Control Variables

To examine if the predictive power of the filtered expected risk premia is affected by various control variables, I take the following frequently used variables into consideration when doing empirical analysis. Overall, these control variables can

[1] `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

[2] `https://sites.google.com/site/haozhouspersonalhomepage/httpsitesgooglecomsitehaozhouspersonalhomepage/vrp-data-update`

be categorized into three types. The first type is the standard control variables including market beta ($BETA$) (under risk-neutral and physical measure), market value (MV), momentum (MOM), and book-to-market ratio ($B2M$). The second type is stock-related variables such as stock trading volume ($SVOLU$), the short-term reversal of Jegadeesh (1990) (REV), the illiquidity of Amihud (2002) ($ILLIQ$), the maximum (MAX) daily return over the previous month proposed by Bali et al. (2011), the minimum (MIN) daily return over the previous month, and the default risk measure developed by Zmijewski (1984) (ZS). The last type is option-related control variables. In particular, I consider the following variables: option trading volume ($OVOLU$) (Pan and Poteshman (2006)), option open interest (OI) (Hong and Yogo (2012)), put-to-all options volume ratio ($P2AR$) (Taylor et al. (2009)), and option-implied short-term (1-month) volatility ($IVOL$), skewness ($ISKEW$), and kurtosis ($IKURT$). The definitions of these control variables are provided in Appendix 3.9.

3.4.2 Risk-Neutral Cumulants

Option-implied cumulants are related to expected stocks' risk premia through the latent underlying risk factors, and therefore, to infer expected risk premia, I first need to calculate risk-neutral cumulants. I use the model-free method proposed by Bakshi and Madan (2000) and Bakshi et al. (2003) to compute risk-neutral cumulants directly from OTM options for each individual stock. In particular, Bakshi and Madan (2000) show that any twice-differentiable payoff function, contingent on the future stock price, can be spanned by a continuum of OTM call and put option prices on that stock. Besides, Bakshi et al. (2003) further show how to calculate risk-neutral cumulants at the second, third and fourth order using the variance, cubic, and quartic contracts.

At time t, I follow Bakshi et al. (2003) and compute the second, third, and fourth-order risk neutral cumulants for each stock i as follows:

$$CUM_{i,t}^{\tau}(2) = e^{r_f \tau} V_{t,\tau} - (\mu_{t,\tau}^{Q})^2 \tag{3.9}$$

$$CUM_{i,t}^{\tau}(3) = e^{r_f \tau} W_{t,\tau} - 3\mu_{t,\tau}^{Q} e^{r_f \tau} V_{t,\tau} + 2(\mu_{t,\tau}^{Q})^3 \tag{3.10}$$

$$CUM_{i,t}^{\tau}(4) = e^{r_f \tau} X_{t,\tau} - 4\mu_{t,\tau}^{Q} e^{r_f \tau} W_{t,\tau} + 6 e^{r_f \tau} (\mu_{t,\tau}^{Q})^2 V_{t,\tau} - 3(\mu_{t,\tau}^{Q})^4 \tag{3.11}$$

where r_f is the risk-free rate, $V_{t,\tau}$, $W_{t,\tau}$, and $X_{t,\tau}$ are the time t prices of τ-maturity variance, cubic and quartic contracts, respectively. The details of these contracts are given in Appendix 3.10. In addition, $\mu_{t,\tau}^{Q}$ is given by the following:

$$\mu_{t,\tau}^{Q} = exp(r_f \tau) - 1 - \frac{exp(r_f \tau)}{2} V_{t,\tau} - \frac{exp(r_f \tau)}{6} W_{t,\tau} - \frac{exp(r_f \tau)}{24} X_{t,\tau} \tag{3.12}$$

3.4.3 Characteristics of the Data

By applying the above proposed partial least squares-based method on the second, third, and fourth-order cumulants with maturities ranging from one month to two years, I get ex-ante filtered expected risk premia (FERP) on all stocks. It is worth pointing out that there is no look-ahead bias in estimating FERP. I then form decile portfolios based on the FERP in each month. Portfolio 1 contains stocks with the lowest FERP, while portfolio 10 contains the highest ones. Besides, a spread portfolio that goes long portfolio 10 and short Portfolio 1 is also formed. Figure 3.1 shows the dynamics of the monthly demeaned expected risk premia filtered from different cumulants for portfolios 1, 5 and 10.

[Figure 3.1 about here]

The top panel of Figure 3.1 presents monthly FERP based on second-order cumulants, the middle panel shows monthly FERP based on second and third-order cumulants, and the monthly FERP based on second, third and fourth-order cumulants is shown in the bottom panel. It is clear to see that there is big variation of FERP for all three panels, which is consistent with the findings of Martin and Wagner (2018). FERP based on second-order cumulants (top panel) generates the smallest dispersion across portfolios among three panels, suggesting that higher-order cumulants (third and fourth-order) also contain future returns-related information cross-sectionally. When comparing the middle and bottom panels; however, it seems that the fourth-order cumulants do not make a big difference.

[Table 3.1 about here]

To examine whether the dispersion in FERP transfers equivalently into future realized risk premia, Table 3.1 reports the average future realized risk premia of decile portfolios that are constructed based on the ex-ante FERP estimated from cumulants at different orders. In particular, in each month, decile portfolios are formed based on the above-mentioned procedure, and these portfolios are held over the next month. Then their equal-weighted and value-weighted monthly realized risk premia are reported in the Table 3.1. Besides, the realized risk premium of the FERP-based high-minus-low spread portfolio is also presented in the Table 3.1. I observe that smaller dispersion in the FERP leads to smaller variation of realized risk premia across portfolios for all three panels of Table 3.1. Moreover, this pattern holds for both the equal-weighted and value-weighted realized excess returns. More importantly, consistent with the Figure 3.1, the FERP estimated only from second-order cumulants (Panel A) generates smaller variation in the realized risk premia across portfolios compared to the results in

Panel B or C. What's more, the realized equal-weighted risk premium on the spread portfolio is 0.89% per month without considering fourth-order cumulants (Panel B), and it becomes 0.86% per month when considering fourth-order cumulants (Panel C), indicating that the fourth-order cumulants are less relevant in forecasting cross-sectional future stock returns.

[Figure 3.2 about here]

Figure 3.2 shows the cumulative realized risk premia of the investment on the spread portfolio that goes long the portfolio with the highest FERP and short the portfolio with the lowest FERP, on the market and on the momentum strategy, respectively. The spread portfolio is constructed based on the FERP estimated from risk-neutral cumulants at different orders. The top panel shows equal-weighted realized risk premia while the bottom panel presents value-weighted realized risk premia. It is clear to see that, also consistent with the results in Table 3.1, the fourth-order risk-neutral cumulants do not make a difference. In what follows, I will mainly focus on the FERP estimated from the second and third-order cumulants.[1] In addition, it is worth mentioning that the spread portfolio achieves better performance than the market and the momentum strategy.

3.5 Filtered Expected Risk Premium and Future Stock Returns

In this section, I focus on cross-sectional analysis and examine the relationship between the ex-ante filtered expected risk premia (FERP) of individual stocks and future stocks' risk premia. FERP is estimated by employing the partial least squares-based algorithm described in the Section 3.3 on the second- and third-order risk-neutral cumulants with maturities ranging from one month to two years. Decile portfolios are formed with the procedures introduced in Subsection 3.4.3. I first summarize the statistics of decile portfolios, and then I implement portfolio sort analysis. After that, the Fama-MacBeth cross-sectional regressions are conducted. Finally, the long-term return predictability is investigated.

[1] The results based on the FERP that are separately estimated from second, third, and fourth-order cumulants are qualitatively similar to the main findings of the paper except that the spread portfolio earns a smaller realized risk premium when only using the information contained in the second, third, or fourth-order cumulants.

3.5.1 Statistics of Decile Portfolios

Panel A of Table 3.2 reports the descriptive statistics of equal-weighted decile portfolios that are constructed based on the ex-ante filtered expected risk premia (FERP). It is clear to see that the average realized equal-weighted monthly risk premia for portfolios 1 to 10 almost monotonically increase with respect to FERP, ranging from 0.26% for portfolio 1 to 1.16% for portfolio 10.[1] The future realized risk premia of two extreme portfolios - portfolio 1 and 10 - are more volatile than that of other eight portfolios. In particular, portfolio 1 has a monthly standard deviation at 4.37, and the counterpart of portfolio 10 is 3.98. In addition, portfolio 1 is left skewed while portfolio 10 is right skewed, with a skewness at -0.80 and 0.16, respectively. The kurtosis of decile portfolios indicates that all ten portfolios are not normally distributed. Besides, the t-statistics show that all decile portfolios except portfolio 1 have significantly non-zero monthly average risk premia. More importantly, the monthly average risk premium of the high-minus-low spread portfolio is about 0.89%, which is statistically significant with t-statistic at 3.20. Furthermore, the realized risk premium of the spread portfolio is also more volatile than all other decile portfolios, with a standard deviation at 4.54, and it is not normally distributed and has a positive skewness.

[Table 3.2 about here]

Panel B of Table 3.2 presents the descriptive statistics of value-weighted portfolios. Similar to Panel A, the realized monthly average risk premia also increase from portfolio 1 to portfolio 10 with respect to the FERP. The two most volatile portfolios are portfolio 1 and 10. However, different to the portfolio 1 in the Panel A, portfolio 1 in the Panel B is right skewed with a monthly skewness at 0.17, which is smaller than that of portfolio 10 in the Panel B. The monthly value-weighted risk premia of all decile portfolios are not normally distributed. Besides, they are also statistically significantly different from zero. More importantly, the spread portfolio still earns a statistically significant risk premium of 0.70% per month with a t-statistic at 2.37. In contrast, this premium and its t-statistic are smaller than their counterparts in Panel A. In what follows, I only present results based on the equal-weighted risk premia.

[1] The one-month Treasury bill rate is used as the risk-free rate.

3.5.2 Portfolio Analysis

3.5.2.1 Characteristics of the Filtered Expected Risk Premium-Sorted Portfolios

The summary statistics in the previous subsections show that there is a considerably large variation in the ex-ante filtered expected risk premia (FERP), rendering it a meaningful sorting criterion. Table 3.3 reports the average firm characteristics of the FERP-sorted decile portfolios. I find that, on average, market values (MV), book-to-market ($B2M$) ratios, momentum (MOM), and the risk-neutral market beta ($BETA^Q$) are not very different across portfolios. However, stocks with the lowest FERP have relatively large physical measure market beta ($BETA^P$), and are also more illiquid ($ILLIQ$) relative to the stocks with the highest FERP even though the differences are insignificant. Stock volumes ($SVOLU$) are characterized by a U-shape across portfolios 1 to 10, and the two extreme portfolios contain the stocks that are more actively traded in the stock market. On the contrary, the short-term reversal (REV) exhibits an inverse U-shape across portfolios with the middle portfolio having a relatively high short-term reversal.

[Table 3.3 about here]

Table 3.3 also shows that the average maximum (MAX) and minimum (MIN) daily excess returns in the previous month are not significantly different across portfolios, suggesting that low (high) FERP does not mimic the proxy of stock overvaluation (undervaluation). Besides, the default risk (ZS) of Zmijewski (1984) does not variate significantly across portfolios. In terms of options-related characteristics, both options trading volume ($OVOLU$) and open interest (OI) are not characterized by monotonicity across portfolios. However, I find that stocks with the lowest FERP exhibit, on average, higher put-to-all options volume ratio ($P2AR$) compared to stocks with the highest FERP, indicating that those lower expected excess return stocks may suffer from short-selling constraints which leads investors resorting to put options, generating a higher put-to-all options volume ratio. These firm characteristics are controlled when doing Fama-MacBeth cross-sectional regressions. The pair-wise correlations between these variables are reported in Appendix 3.12.

3.5.2.2 Risk-Adjusted Portfolio Returns

I examine whether realized risk premia of the ex-ante filtered expected risk premium (FERP)-based portfolios can be explained by commonly used risk factors.

For this purpose, I start from the capital asset pricing model (CAPM)

$$r_i - r_f = \alpha_i + \beta_{i,MKT} MKT + \epsilon_i$$

and the Fama-French three-factor model (Fama and French (1993))

$$r_i - r_f = \alpha_i + \beta_{i,MKT} MKT + \beta_{i,SMB} SMB + \beta_{i,HML} HML + \epsilon_i$$

and the Carhart four-factor model (Carhart (1997))

$$r_i - r_f = \alpha_i + \beta_{i,MKT} MKT + \beta_{i,SMB} SMB + \beta_{i,HML} HML + \beta_{i,MOM} MOM + \epsilon_i$$

and the Fama-French five-factor model (Fama and French (2016))

$$r_i - r_f = \alpha_i + \beta_{i,MKT} MKT + \beta_{i,SMB} SMB + \beta_{i,HML} HML + \beta_{i,RMW} RMW + \beta_{i,CMA} CMA + \epsilon_i$$

where $r_i - r_f$ denotes portfolio returns in excess of one-month treasury bill rates, and MKT, SMB, and HML are the usually used factors of market, size, and value, respectively. MOM is the factor of momentum. RMW and CMA are two recently proposed factors of profitability and investment, respectively.

In addition, I also consider the widely studied option-implied factor - variance risk premia (VRP), which is proposed by Bollerslev et al. (2009).

$$r_i - r_f = \alpha_i + \beta_{i,MKT} MKT + \beta_{i,SMB} SMB + \beta_{i,HML} HML + \beta_{i,VRP} VRP + \epsilon_i$$

where VRP is variance risk premium, which is defined as the difference between the risk-neutral and objective expectations of realized variance on the S&P 500 index. There is evidence that the VRP factor outperforms the classical Fama-French three, five factors, and the Carhart momentum factor in explaining most of anomalies (e.g., Bollerslev et al. (2014), Zhou (2017), and Londono and Zhou (2017)).

Besides, Stambaugh and Yuan (2016) recently proposed a mispricing-factor model in which they find that the two mispricing factors $MGMT$ and $PERF$ outperform the commonly studied Fama-French five-factor and the Carhart four-factor models in explaining most of anomalies. Therefore, the last model I consider is the mispricing model of Stambaugh and Yuan (2016):

$$r_i - r_f = \alpha_i + \beta_{i,MKT} MKT + \beta_{i,SMB} SMB + \beta_{i,MGMT} MGMT + \beta_{i,PERF} PERF + \epsilon_i$$

where the two mispricing factors, $MGMT$ and $PERF$, are constructed by averaging rankings within two clusters exhibiting the greatest co-movement in long-short returns. These two mispricing factors aggregate information across 11 well-known anomalies. In particular, the $MGMT$ factor aggregates the information contained in the quantities that firms' managements can affect directly, while the $PERF$ factor summarizes the information that is related more to performance and is less directly controlled by management.[1]

[Table 3.4 about here]

Panels A, B, C, D, E and F of Table 3.4 report risk-adjusted alphas and factor loadings of regressing portfolios' risk premia on the market factor, on the Fama-French three factors, on the Carhart four factors, on the Fama-French five factors, on the variance risk premia (VRP) factor, and on the mispricing factors ($MGMT$ and $PERF$), respectively.[2] In terms of risk-adjusted alphas, I find that the portfolio with the lowest FERP stocks significantly under-performs the portfolio with the highest FERP stocks. In each of the six models above, the monthly risk-adjusted alphas increase monotonically from portfolio 1 to portfolio 10, and the high-minus-low spread portfolio earns a positive, economically substantial, and statistically significant alpha. Specifically, the spread portfolio's alpha is 0.96% per month (t-stat: 3.33) in the CAPM model, is 0.96% per month (t-stat: 3.41) in the Fama-French three-factor model, is 1.06% per month (t-stat: 3.75) in the Carhart four-factor model, is 0.88% per month (t-stat: 3.05) in the Fama-French five-factor model, is 1.07% per month (t-stat: 3.50) in the model with variance risk premia factor, and is 1.13% per month (t-stat: 3.69) in the mispricing model of Stambaugh and Yuan (2016).

Regarding the factor loadings in different models with respect to the market (MKT), size (SMB), value (HML), momentum (MOM), profitability (RMW), investment (CMA), variance risk premia (VRP), and the mispricing factors $MGMT$ and $PERF$, I find that these commonly used risk factors, on average, are unable to explain the dynamics of the high-minus-low spread portfolios' risk premia, indicating that risk-neutral cumulants indeed contain useful future returns-related information which is not captured by the commonly used pricing factors.

[1] The data of these two mispricing factors are obtained from Robert F. Stambaugh's personal webpage at `http://finance.wharton.upenn.edu/~stambaug/`.

[2] The two mispricing factors are only available up to December of 2016, and hence the results in Panel F based on the sample from January 1996 to December 2016.

3.5.3 Relations to Risk-Neutral Volatility, Skewness, and Kurtosis

The ex-ante expected risk premium is estimated by extracting information from option-implied cumulants at different orders, which are related but different to commonly used standardized risk-neutral moments such as volatility, skewness and kurtosis. Moreover, I use risk-neutral cumulants with maturities ranging from one month to two years, which is very different from existing empirical studies focusing on the short-term (1-month maturity) risk-neutral moments. To show that the filtered expected risk premium (FERP) used in this paper is not a mimic of risk-neutral moment, I implement double-sort portfolio analysis to make sure that the positive relationship between the FERP and future realized stock returns is robust after controlling for risk-neutral volatility, skewness, or kurtosis in this section.

3.5.3.1 Filtered Expected Risk Premium and Risk-Neutral Volatility

To control for risk-neutral volatility, I first sort all stocks at the end of each month into quintile portfolios based independently on the filtered expected risk premium (FERP) and risk-neutral volatility, respectively. Then 25 portfolios are formed based on the intersection of the two types of portfolios. These portfolios are held over the next month and their average realized monthly equal-weighted risk premia are reported in the Table 3.5. Besides, Table 3.5 also reports the high-minus-low spread portfolios' risk premia based on the FERP and on risk-neutral volatility, respectively.

[Table 3.5 about here]

Results in Table 3.5 show that the positive relationship between the FERP and future stocks' realized risk premia remain even after keeping risk-neutral volatility constant, which holds for all levels of risk-neutral volatility. More importantly, the high-minus-low spread portfolio with respect to the FERP continues to earn economically and statistically significant positive returns. Specifically, for low risk-neutral volatility stocks, the FERP-based high-minus-low spread portfolio earns a monthly risk premium of 0.58% (t-stat: 2.96), whereas for high risk-neutral volatility stocks, it earns a monthly risk premium of 0.99% (t-stat: 2.96). In addition, I observe that the FERP-based spread portfolio tends to earn higher risk premium with the increasing of risk-neutral volatility, suggesting that the predictive power of the FERP is stronger when investors expect more volatile of risk-neutral stock returns. Regarding risk-neutral volatility-based (IV-based) spread portfolios, I find some evidence of the negative relationship between the risk-neutral volatility and future stocks' risk premia as for all levels of the FERP.

Specifically, the risk-neutral volatility-based spread portfolios earn negative risk premia, and they are statistically significant in four out of five cases.

3.5.3.2 Filtered Expected Risk Premium and Risk-Neutral Skewness

To control for risk-neutral skewness, I repeat the above procedures used in analyzing risk-neutral volatility. Table 3.6 presents future realized risk premia on portfolios that are formed by implementing double-sort independently on the filtered expected risk premium (FERP) and the short-term risk-neutral skewness. Similar to the findings in Table 3.5, I find that for each level of risk-neutral skewness, the high-minus-low spread portfolio with respect to the FERP still earns a statistically significant positive risk premium. For example, for low risk-neutral skewness stocks, the FERP-based spread portfolio earns a monthly risk premium of 0.74% (t-stat: 3.53), for middle risk-neutral skewness stocks, it earns a monthly risk premium of 0.69% (t-stat: 2.72), and for high risk-neutral skewness stocks, the monthly risk premium earned by the spread portfolio is 0.71% (t-stat: 2.89).

[Table 3.6 about here]

In addition, it is worth pointing out that Table 3.6 also presents strong evidence of the negative relationship between the risk-neutral skewness and future stocks' risk premia. Specifically, for each level of the FERP, the high-minus-low (low-minus-high) spread portfolio with respect to the risk-neutral skewness earns a statistically significant negative (positive) monthly risk premium, which is consistent with skewness preference theory. Besides, these results also echo the findings of Bali and Murray (2013) and Conrad et al. (2013). What's more, the low-minus-high spread portfolio based on the risk-neutral skewness yields an excess return about 0.60% per month in Table 3.6, which is also close to the finding of Stilger et al. (2016) who show that the monthly excess return of a spread portfolio based on the short-term risk-neutral skewness is 0.61%. Overall, I find that the positive relationship between the FERP and future stocks' realized risk premia is not affected by taking the short-term risk-neutral skewness into consideration.

3.5.3.3 Filtered Expected Risk Premium and Risk-Neutral Kurtosis

I now examine whether the positive relationship found in the previous subsections is also robust to the risk-neutral kurtosis. For this purpose, I implement a similar double-sort analysis as before and results are reported in Table 3.7. Similarly, I find that holding risk-neutral kurtosis constant, the filtered expected risk premium (FERP) again continues to be positively related to future stocks' risk premia: for all levels of risk-neutral kurtosis, the FERP-based high-minus-low spread portfolios remain to earn statistically significant positive risk premia. For example, for low risk-neutral kurtosis stocks, the FERP-based spread portfolio earns a risk premium of 0.77% per month (t-stat: 2.85), whereas for high risk-neutral kurtosis stocks, it earns a monthly risk premium of 0.61% (t-stat: 3.30). Besides, Table 3.7 also shows some evidence of the negative relationship between risk-neutral kurtosis and future stocks' risk premia even though this negative relationship is insignificant.

[Table 3.7 about here]

In summary, the positive relationship between the ex-ante FERP and future stocks' realized risk premia is robust even after controlling for short-term risk-neutral volatility, skewness, and kurtosis, suggesting that the FERP is not a mimic of widely studied short-term risk-neutral moments. It can be viewed as a new pricing factor embedded in option price panels. Moreover, the magnitude of the FERP-related premium is larger than the premium related to the single risk-neutral moment reported in the existing literature, which is consistent with our expectation because the FERP is estimated from risk-neutral cumulants at different orders with maturities instead of focusing only on the short-term risk-neutral volatility, skewness, or kurtosis.

3.5.4 PLS and Principal Component Analysis

The ex-ante filtered expected risk premium (FERP) is estimated by using a partial least squares (PLS)-based method, which allows to aggregate future returns-related information embedded in the large cross-section of risk-neutral cumulants efficiently. However, an alternative way to aggregate information contained in risk-neutral cumulants is the principal component analysis (PCA) approach. Moreover, PCA provides a convenient way to summarize the common variation of a large set of risk-neutral cumulants. But, this common factor, usually the first principal component, may not be useful for predicting future stocks' returns even though it can explain most part of the variation in cumulants. In contrast to PCA, this paper's PLS-based algorithm identifies a factor with the best ability to predict future stocks' returns and it condenses the cross-section of option-implied cumulants according to their covariances with the future risk premium. More importantly, PLS-based approaches only extract returns-related information from risk-neutral cumulants, while PCA would mix returns-related and returns-unrelated information embedded in risk-neutral cumulants. Nevertheless, I still wonder whether the FERP captures different information from the first principal component of risk-neutral cumulants on future stock returns. I examine whether the positive relationship between the FERP and future stocks' risk premia still holds after controlling for the first principal component of risk-neutral cumulants. For this purpose, I first compute the first principal component of the second, third, and fourth-order risk-neutral cumulants with maturities ranging from 1 month to 2 years, and then I implement double-sort portfolio analyses as before.[1] Results are reported in Table 3.8.

Panel A, B, and C of Table 3.8 presents realized portfolios' risk premia from double-sort analysis. In particular, all stocks are sorted into quintile portfolios based independently on the filtered expected risk premium (FERP) and on the first principal component of second, third, or fourth-order risk-neutral cumulants, respectively. Then, 25 portfolios are formed based on the intersection of the two types of portfolios. These portfolios are held over the next month and their monthly average risk premia are calculated. Overall, results in Table 3.8 indicate that the positive relationship between the FERP and future stocks' risk premia remains even after controlling for the first principal component of second, third, and fourth-order risk-neutral cumulants. Specifically, I observe in Panel A that holding the first principal component of second-order cumulants constant, the FERP continues to be positively related to future stock returns: for all levels of the first principal component of the second-order risk-neutral cumulants, the average monthly risk premia for portfolio 1 to 5 increase monotonically with respect to the FERP, and more importantly, the FERP-based high-minus-low spread portfolios remain to earn economically and statistically significant positive risk premia. For example, for the stocks with the lowest first principal component of the second-order risk-neutral cumulants, the FERP-based spread portfolio earns a risk premium of 0.59% per month (t-stat: 3.05), whereas for the stocks with the highest first principal component of the second-order risk-neutral cumulants, it earns a monthly risk premium of 1.05% (t-stat: 3.19). Interestingly, Panel A of Table 3.8 also shows some evidence of the negative relationship between the first principal component of the second-order risk-neutral cumulants and future stock returns as for all levels of the FERP. However, such a relationship is only significant when the FERP is low.

[Table 3.8 about here]

Similarly, the positive relationship between the FERP and future stocks' risk premia remains when I move to Panel B and C of Table 3.8. In particular, holding the first principal component of the third-order risk-neutral cumulants (fourth-order risk-neutral cumulants) in Panel B (Panel C) constant, the FERP

[1] I only consider the first principal component of the risk-neutral cumulants at different orders because the first principal component accounts most part of variation in risk-neutral cumulants. For example, the first principal component explains about 95%, 72%, and 94% of the variation of the second, third, and fourth-order risk-neutral cumulants, respectively.

continues to be positively related to future stocks' risk premia. Moreover, the magnitude of portfolios' risk premia in Panel B and C are also comparable with the results in Panel A. For example, for stocks with the lowest first principal component of the third-order (fourth-order) risk-neutral cumulants in Panel B (Panel C), the FERP-based spread portfolio earns a monthly risk premium of 0.79% (0.63%) with t-statistic equals 3.39 (3.19), whereas for stocks with the highest first principal component of the third-order (fourth-order) risk-neutral cumulants, it earns a monthly risk premium of 1.06% (1.07%) with t-statistic at 3.56 (3.26), and these values are close to their counterparts in Panel A.

To summarize, Table 3.8 presents strong evidence that the ex-ante FERP estimated by employing the aforementioned PLS-based algorithm on a large set of risk-neutral cumulants captures different information from the first principal component of the second, third, or fourth-order risk-neutral cumulants on future stock returns. The positive relationship between the FERP and future stocks' risk premia is still significant even after taking the first principal component of risk-neutral cumulants into account. More importantly, the PCA technique is unable to extract useful information embedded in a large cross-section of risk-neutral cumulants on future stock returns.

3.5.5 Fama-MacBeth Cross-Sectional Analysis

The previous subsections focus on portfolio-sort analyses and show that the filtered expected risk premium (FERP) is significantly positively related to future stock returns. Stocks exhibiting the lowest FERP significantly under-perform stocks exhibiting the highest FERP. In this subsection, I further examine how robust the positive relationship between the FERP and future stocks' risk premia is by using a set of Fama-MacBeth cross-sectional regressions (Fama and MacBeth (1973)). In contrast to portfolio-sort analysis, the Fama-MacBeth regression allows for extensive controls of variables that have been found to have predictive power for future stock returns. Specifically, I consider three types of control variables: (1) the frequently used variables such as market value (MV), book-to-market ratio ($B2M$), momentum (MOM), and market beta under physical ($BETA^P$) and risk-neutral ($BETA^Q$) measure; (2) the stock-related variables, including stock trading volume ($SVOLU$), the short-term reversal proposed by Jegadeesh (1990) (REV), illiquidity of Amihud (2002) ($ILLIQ$), the maximum (MAX) and minimum (MIN) daily return over the past month in Bali et al. (2011), and firms' default risk developed by Zmijewski (1984) (ZS); and (3) the option-related variables such as option trading volume ($OVOLU$) (Pan and Poteshman (2006)), option open interest (OI) (Hong and Yogo (2012)), put-to-all options volume ratio ($P2AR$) (Taylor et al. (2009)), and option-implied short-term volatility ($IVOL$), skewness ($ISKEW$) and kurtosis ($IKURT$). For each month of the sample, I run cross-sectional regressions of realized risk premia on lagged ex-ante FERP and a series of control variables. Table 3.9 reports the average slope coefficients estimated from these monthly cross-sectional regressions as well as their t-statistics computed using Newey-West standard errors.

Model 1 (M1) of Table 3.9 uses the filtered expected risk premium (FERP) as the only explanatory variable, documenting a significant positive relationship between the FERP and future stocks' risk premia. Specifically, the magnitude of the FERP coefficient is 0.128 with a t-statistic at 3.17. The adjusted R^2 is about 4.8% (t-stat: 10.78). Note that the spread in average FERP between the highest and the lowest deciles in Table 3.2 is 7.285. Therefore, the reported coefficient on the FERP implies that the average return differential between the extreme FERP-based decile portfolios should be 0.93 ($= 7.285 * 0.128$) per month, which is very close to the spread return reported in Table 3.2, 0.89.

In model 2 (M2), I introduce a set of commonly used control variables, namely risk-neutral market beta ($BETA^Q$), market value (MV), momentum (MOM), and book-to-market ratio ($B2M$), into regression.[1] I find that the coefficient on the FERP remains positive and highly statistically significant, 0.080 (t-stat: 2.26). The adjusted R^2 increases to 15.5% (t-stat: 20.92). Moreover, I also find that both the risk-neutral market beta and momentum are significantly positively related to the future stocks' risk premia, which is consistent with finding in the previous literature. Model 3 (M3) additionally controls for the stock trading volume ($SVOLU$), and it shows that stock trading volume is significantly negatively related to the future stocks' risk premia, but it does not affect the significant positive relationship between the FERP and future stocks' risk premia. The coefficient on the FERP is 0.08 (t-stat: 2.42) and the adjusted R^2 is 16.5% (t-stat: 22.08) in this case. Model 4 (M4) additionally controls for the short-term reversal (REV). In this case, the magnitude of the coefficient on the FERP is 0.082 (t-stat: 2.34), which is smaller than that in the benchmark model (M1), but it is still statistically significant. The adjusted R^2 is about 17.3% (t-stat: 23.49). Furthermore, the coefficient on the short-term reversal is negative and statistically significant, -0.049 (t-stat: -14.41), which is consistent with the finding of Jegadeesh (1990). I additionally control for illiquidity ($ILLIQ$) in Model 5 (M5) and find that the positive relationship between the FERP and future stocks' risk premia still remain. More importantly, such positive relationship is statistically significant, 0.084 (t-stat: 2.41). The adjusted R^2 is 16.1% (t-stat: 21.96). Bali et al. (2011) use the maximum daily return (MAX) over the past month as a proxy for extreme positive skewness and find it relates to future stock returns. I

[1]The results with physical measure beta $BETA^P$ is reported in the Appendix 3.12, and the main findings of this paper are independent on the type of the market beta. However, the risk-neutral market beta is positively significantly related to the future stock returns whereas the coefficient on the physical measure market beta is insignificant.

add this variable as an additional control variable in Model 6 (M6). The coefficient on the FERP is still positive and significant, 0.090 (t-stat: 2.73). However, the coefficient on MAX is insignificant. The adjusted R^2 is 16.5% (t-stat: 22.05). As a comparison, I replace MAX with the minimum daily return (MIN) over the past month in Model 7 (M7). I find that the coefficient on the FERP is close to that in M6. More importantly, this coefficient remains positive and statistically significant, 0.085 (t-stat: 2.52). The coefficient on MIN is also significant but with negative sign. The adjusted R^2 in this case is about 16.9% (t-stat: 22.81). I then introduce firms' default risk measured by using the Zmijewski (1984) Z-score (ZS) in Model 8 (M8), and I find that firms' default risk is significantly and negatively related to the future stock returns. But, more importantly, the coefficient on the FERP is still positive and significant, 0.078 (t-stat: 2.24) and the adjusted R^2 is 16.5% (t-stat: 21.55). To summarize, in Models 2-8, I additionally control a set of stock-related variables except the frequently used control variables and find that the relationship between the ex-ante FERP and future stocks' risk premia remains positive and significant across models. Moreover, the coefficients on the FERP are consistent across different models.

[Table 3.9 about here]

In Models 9-12, I add several widely studied option-related variables except the aforementioned commonly used control variables into regressions. Specifically, Model 9 (M9) additionally controls for option trading volume ($OVOLU$). Easley et al. (1998) and Pan and Poteshman (2006) present strong evidence that option trading volume contains information about future stock prices. After controlling for $OVOLU$, the coefficient on the FERP is 0.073 (t-stat: 2.10), which is still statistically significant. The adjusted R^2 is about 16.3% (t-stat: 21.72). However, the coefficient on option trading volume is insignificant. As a complement, in Model 10 (M10) I use option open interest (OI) to replace $OVOLU$. Moreover, Hong and Yogo (2012) find that option open interest is related to future stock return. I find that the coefficient on the FERP remains positive and statistically significant, 0.075 (t-stat: 2.14). The adjusted R^2 is still 16.3% (t-stat: 21.61). What's more, the coefficient on OI is also insignificant. Next, Model 11 (M11) additionally controls for put-to-all options volume ratio ($P2AR$), which is often used as a measure of investors' hedging demand on stocks and has been proven negatively related to the future stock returns (see Taylor et al. (2009) and Stilger et al. (2016)). I find the positive relationship between the FERP and future stocks' risk premia is still statistically significant, 0.079 (t-stat: 2.16). Moreover, the coefficient on $P2AR$ is indeed significant and negative, -1.610 (t-stat: -6.64), which echoes the findings in the literature. The adjusted R^2 in this case is 16.3% (t-stat: 21.73).

In addition, Model 12 (M12) introduces extensively studied option-implied short-term volatility ($IVOL$), skewness ($ISKEW$), and kurtosis ($IKURT$) as extra control variables. Results show that the coefficient on the FERP remains positive and statistically significant, 0.065 (t-stat: 2.08), confirming that the positive relationship between the FERP and future stocks' risk premia is not affected by the relationship between risk-neutral volatility, risk-neutral skewness, or risk-neutral kurtosis and future stock returns. Moreover, the negative coefficients on $IVOL$, $ISKEW$, and $IKURT$ are also consistent with the results in Table 3.5, 3.6, and 3.7 even though these coefficients are insignificant. The adjusted R^2 is 19.0% (t-stat: 23.92). Finally, I put all the above-mentioned variables into Model 13 (M13), and again, the coefficient on the FERP is still positive and significant, 0.080 (t-stat: 2.78). The adjusted R^2 increases to 24.8% (t-stat: 30.64).

To summarize, the Fama-MacBeth regressions results in Table 3.9 confirm the main finding: the higher the filtered expected risk premium (FERP), the larger future realized risk premium, as the coefficient on the FERP remains positive and statistically significant across all regressions. In addition, it is worth pointing out that both risk-neutral market beta ($BETA^Q$) and momentum (MOM) are significantly and positively related to the future stocks' risk premia although they do not affect the positive relationship between the FERP and future stocks' risk premia, suggesting that the FERP captures different information on future stock returns from these two factors.

3.5.6 Long-Term Performance of FERP-Sorted Portfolios

The above analyses show that the filtered expected risk premium (FERP) can predict the following month's realized risk premium. How long could the predictive power of the FERP last? To answer this question, I examine the long-term performance of the FERP-sorted portfolios. Specifically, at the end of each month t, stocks are sorted into decile portfolios based on their FERP, and a high-minus-low spread portfolio is also formed. Then, these portfolios are held over $t + k$ months, where k equals to 1, 2, 3, 6, and 12. I calculate their equal-weighted monthly risk premia as well as risk-adjusted alphas, and the results are reported in Table 3.10. I find that the FERP-based high-minus-low spread portfolio's risk premium and risk-adjusted alphas are economically substantial and highly statistically significant only in the first month. Recall that the first post-ranking month ($k = 1$) is the one analyzed in the previous subsections. Then the monthly risk premium of the spread portfolio is only marginally significant in the second post-ranking month ($k = 2$) and become small and insignificant in the third post-ranking month ($k = 3$), but the risk-adjusted alphas are still significant in the second month although they are only marginally significant in the third month. However, the magnitude of the risk-adjusted monthly risk premium of the spread portfolio is smaller than its counterpart in the first post-ranking month even though it remains marginally significant until the six post-ranking month ($k = 6$). In summary, these results show that the predictive power of the FERP is only temporary and it diminishes within two months, suggesting that the stock market incorporates the information contained in the options market quickly.

[Table 3.10 about here]

3.6 Robustness Analysis

3.6.1 Subsample Analysis

In this section, I investigate the robustness of the main findings in Section 3.5. I first test the robustness of the above results to alternative data samples. Specifically, the full data sample is firstly split into two equal-length subsamples. In particular, the first subsample covers the period from January 1996 to December 2006, and the second subsample ranges from January 2007 to December 2017. I then repeat the portfolio-sort analysis as in the previous section for these two new subsamples. Table 3.11 presents the average monthly realized portfolios' risk premia and risk-adjusted alphas for each of subsample.

[Table 3.11 about here]

Overall, Table 3.11 shows that the filtered expected risk premium (FERP) continues to be positively related to future stocks' risk premia for both subsamples. Specifically, results in Panel A based on the first-half sample, showing that the average monthly risk premia, the Fama-French three-factor (Fama and French (1993)) adjusted alphas, and the Carhart four-factor (Carhart (1997)) adjusted alphas for decile portfolios 1 to 10 increase with respect to the FERP. Moreover, the FERP-based high-minus-low spread portfolio remains to earn economically and statistically significant positive risk premium. For example, the spread portfolio yields the Carhart four-factor adjusted alpha of 0.90% per month (t-stat: 2.08) in Panel A, which is comparable with the finding from full sample in Table 3.4, 1.06% (t-stat: 3.75). As a comparison, Panel B reports the average monthly risk premia and risk-adjusted alphas for the sample ranging from January 2007 to December 2017. Similarly, the FERP-based high-minus-low spread portfolio earns the Carhart four-factor adjusted alpha of 1.27% per month (t-stat: 3.62). Interestingly, the magnitude of the Carhart four-factor adjusted alpha for the second-half data sample increased relative to the benchmark results in Table 3.4.

In summary, the main findings of the paper are robust to these two alternative data samples.

3.6.2 Single-Factor Model Case

The filter expected risk premium (FERP) used in the previous sections is estimated based on a two-factor model, i.e., $L = 2$ in equation (3.8). The model framework with two latent factors is widely used in pricing options and has been extensively studied in the option pricing literature (e.g., Duffie et al. (2000), Bates (2000), Feunou et al. (2013)). Given this paper's crucial assumption that risk-neutral cumulant is a linear function of the latent underlying risk factors (equation (3.8)) is inspired by the implication of affine reduced-form option pricing models, it is reasonable to keep the model setup consistent with the option pricing framework, i.e., consider the same number of underlying risk factors as in the option pricing literature. Moreover, the expected excess return on individual stock in Martin and Wagner (2018) is also equipped with a two-factor structure. However, in the literature of option pricing, one-factor model is also frequently used (e.g., Heston (1993), Pan (2002), and Broadie et al. (2007)).[1] Therefore, the second robustness check I carry out is to do cross-sectional analysis by using the FERP estimated from one-factor model specification (i.e., $L = 1$ in equation (3.8)). Table 3.12 reports the average monthly portfolios' realized risk premia and risk-adjusted alphas for decile portfolios as well as for the high-minus-low spread portfolio.

Consistent with the findings in the previous sections, Table 3.12 shows that both the average monthly risk premia and risk-adjusted alphas increase from portfolio 1 to 10 with respect to the FERP even though the FERP is estimated under the single-factor model setup. More importantly, the high-minus-low spread portfolio remains to earn economically and statistically significant positive return under each of the three scenarios in Table 3.12. It is worth pointing out that the magnitude of the monthly risk premia and the risk adjusted alphas are smaller in the single-factor case than that in the benchmark model (Table 3.4), where the FERP is estimated based on the two-factor setup. However, the main finding that the FERP is significantly positively related to future stocks' risk premia is robust to this alternative single-factor model specification.

[Table 3.12 about here]

[1] Except one and two-factor setup, several three-factor models have also been explored in pricing options recently. For example, Andersen et al. (2015a), Andersen et al. (2015b), and Gruber et al. (2015). But, in these models, such as Andersen et al. (2015b), they show that only one factor contains relevant information about future stock returns.

To further make sure that the main findings in Section 3.5 are robust to the FERP estimated under the one-factor model setup, I also implement Fama-MacBeth cross-sectional regressions by introducing a set of control variables discussed in the previous section. But this time decile portfolios are formed based on the FERP which are extracted from the second and third-order risk-neutral cumulants under the single-factor model framework. Table 3.13 reports the average slope coefficients estimated from monthly cross-sectional regressions as well as their t-statistics computed using Newey-West standard errors. I observe that the coefficient on the FERP is positive and significant across all thirteen models, which is consistent with the findings in Table 3.9. Put differently, these findings in Table 3.13 support the prior argument that there is significant positive relationship between the ex-ante FERP and future stocks' risk premia even after controlling for commonly used as well as various stock and option related variables.

[Table 3.13 about here]

3.6.3 Discussion of Option Pricing Implication of Filtered Latent Risk Factors

The findings of the paper are based on the model setup in Section 3.2. Although this paper is not focused on proposing a theoretical model to price options, the specifications of equations (3.4) and (3.8) provide some insights of option prices. Latent risk factors $F_{i,t}$ in the equation (3.4) should drive in principle both stocks' and options' prices simultaneously. Moreover, the above analyses indeed confirm that the filtered latent risk factors are priced in the stock market, and therefore, I investigate in this part whether they are also priced in the option market. However, as pointed out in Section 3.2, this paper does not provide a specific option pricing model and instead exploits the linear relationship between risk-neutral cumulants and latent risk factors implied by the general affine option pricing framework, suggesting that it is unable to price specific option contracts. In this case, to check the option pricing performance of the filtered latent risk factors, I concentrate on investigating if the filtered future returns-related latent risk factors are consistent with the assumption of equation (3.8).[1]

[1]Using risk-neutral cumulants at different orders with various maturities to estimate (almost) affine option pricing model is suggested by Feunou and Okou (2017), and therefore, if the model-implied risk-neutral cumulants are consistent with data-implied risk-neutral cumulants, then the filtered latent risk factors of the paper can be viewed as risk factors driving option prices under some affine option pricing models.

Recall that the estimation procedures in Section 3.3 only identify the (cross-sectionally) demeaned cumulants, and therefore, I examine whether the model-implied risk-neutral cumulants (calculated as the product of filtered returns-related latent risk factors and factor loadings in equation (3.8)) fit the data-implied demeaned risk-neutral cumulants (calculated with the model-free method of Bakshi et al. (2003)). Figure 3.5 plots the time-series of (cross-sectional average) fitted errors, defined as the difference between data-implied risk-neutral cumulant and the model-implied risk-neutral cumulant, for all stocks. Overall, it is clear to see that the fitted errors on average are close to zero for risk-neutral cumulants at different orders with various maturities, suggesting that the filtered returns-related latent risk factors also characterize the properties of option prices under affine option pricing framework.

[Figure 3.5 about here]

In addition, I also examine option pricing performance of the filtered returns-related latent risk factors for individual stocks. Figure 3.6 shows the dynamics of data-implied as well as model-implied risk-neutral (demeaned) cumulants at different orders with maturities at 1 month and 1 year for Apple Inc. Again, I observe that the filtered latent risk factors perform very well in fitting the real data-implied cumulants. Moreover, I find that this pattern also holds for other individual companies such as Microsoft Corporation, JP Morgan Chase & Co, NIKE Inc., Walmart Inc., and so on. See Appendix 3.12 for details.

[Figure 3.6 about here]

3.7 Potential Explanations

In this section, I examine the source of the predictive power of the filtered expected risk premium (FERP). I investigate the characteristics of under-perform stocks and put forward a potential mechanism along with empirical tests to explain the positive relationship between the FERP and future stocks' risk premia by drawing insight from the sequential trade model of Easley et al. (1998). In fact, the theoretical literature on the informational role of options includes Back (1993), Easley et al. (1998), Cao (1999), and among others.

3.7.1 Relation to the Expected Return of Martin and Wagner (2018)

This paper proposes a PLS-based method to estimate (demeaned) expected risk premia on individual stocks by filtering returns-related information embedded in risk-neutral cumulants, and it ends up with estimates of the infeasible best forecasts of future stocks' risk premia. Put differently, the FERP can be viewed as a predictor of future stock's risk premium. Different from this paper's estimation procedure, Martin and Wagner (2018) instead derive an equation of the expected excess return on individual stocks in terms of risk-neutral volatility at the market and individual level under mild assumptions. Moreover, they show that the expected excess return in their paper has a better out-of-sample performance in forecasting future realized returns than the traditional stock return predictors such as size, book-to-market ratio and so on. Given the FERP is also significantly positively related to future stocks' risk premia after controlling for firm level characteristics, I examine whether the FERP in this paper is related to the calculated expected excess return in Martin and Wagner (2018). I first calculate monthly expected excess return on all individual stocks in my sample by using the method proposed by Martin and Wagner (2018) [equation (17) in Section I of their paper]. Although the expected risk premium in this paper is filtered by using risk-neutral cumulants at different orders with various maturities, I find that the FERP of the high-minus-low spread portfolio in this paper is highly correlated with the equal-weighted expected stocks' excess return in Martin and Wagner (2018) and the expected market risk premium in Martin (2017), respectively, which are calculated only based on 1-month maturity risk-neutral variance.[1]

[Figure 3.3 about here]

Figure 3.3 plots several series of expected risk premia. The black solid line is the FERP of the high-minus-low spread portfolio in this paper, the blue dashed line is the equal-weighted expected risk premia on all stocks, and the red dash-dot line is the expected market risk premium (S&P 500 index), where the latter two expected risk premia are calculated with the method proposed by Martin and Wagner (2018) [equations (13) and (17) in their paper]. It is clear to see that

[1]I also investigate the relationship between the FERP and the calculated expected excess return in Martin and Wagner (2018) for individual stocks, and find that, on average, they are positively related, but the relationship is insignificant. Specifically, I regress FERP on the calculated expected excess returns in Martin and Wagner (2018) cross-sectionally and then I calculate the time-series average of the coefficient on the calculated expected excess return of Martin and Wagner (2018). The coefficient, on average, is positive but insignificant.

the FERP on the spread portfolio is highly correlated with the other two series.[1] In particular, the correlation between the FERP on the spread portfolio and the equal-weighted expected risk premium is 51.5%, and it becomes 47.8% when I replace the equal-weighted expected risk premium with the expected market risk premium. Loosely speaking, these high correlations indicate that the strong predictive power of the FERP in this paper is consistent with the findings of Martin and Wagner (2018) who show that their calculated expected risk premium has a better out-of-sample performance than traditional stock return predictors in forecasting future stock returns.

3.7.2 A Potential Mechanism – Informed Trading

Options contribute to price discovery because they allow traders to better align their strategies with the sign and magnitude of their information. For example, some informed investors may have negative information about some stocks and hence they would like to short sell these stocks. However, these stocks may too costly or too risky to sell short due to short-selling constraints, leading informed investors resorting to the option market. As a result, in line with Miller (1977), short-selling constraints hinder the price mechanism from reflecting these investors' beliefs. Moreover, the argument that the options market attracts informed investors by mitigating short-sale constraints is also consistent with the claim in Black (1975). Therefore, the predictability of the filtered expected risk premium (FERP) may reflect the trading activity of informed traders who choose to trade options before trading stocks due to short-selling constraints. In this way, option prices carry information that leads stock price movements, which is consistent with the sequential trade model of Easley et al. (1998).[2] In addition, Johnson and So (2012) point out that equity short-sale constraints lead informed investors to trade options more frequently for negative signals than positive signals.

To explain this paper's findings, I assume there are at least some informed investors in the market without loss of generality.[3] Under this assumption, for

[1] The reason why the FERP of the high-minus-low spread portfolio is more volatile compared to the expected market risk premium and to the equal-weighted expected risk premia on all individual stocks in S&P 500 index is that the spread portfolio only contains about 92 stocks that are included in two extreme portfolios, whose expected risk premia are more volatile because of sorting procedure. When the spread portfolio is formed based on quintile portfolios, the volatility of the FERP of the spread portfolio is close to that of the equal-weighted expected risk premia on individual stocks, with standard deviations at 4.36% and 4.25%, respectively.

[2] In the setup of Easley et al. (1998), two types of traders, informed and uninformed, can trade both options and stocks, but the model assumes there are at least some informed investors choose to trade options before trading stocks, and hence option prices contain information that it is not embedded in stock prices.

[3] There is a large number of papers that have both theoretically and empirically explored the

the above conjectured mechanism to be valid, several conditions are necessary to hold. First, stocks characterized by higher short-selling constraints should be the ones negatively perceived by informed investors, and hence generate lower expected and future realized risk premia. Second, informed investors resorting to the option market due to short-selling constraints would imply that those highly short-sale constrained stocks should exhibit more actively trading in its options than stocks. Moreover, based on the prediction of Easley et al. (1998), the FERP should also exhibit greater predictability when options are more liquid relative to the underlying stocks.

3.7.2.1 Short-Selling Constraints and Portfolio Returns

The crucial necessary condition is that stocks characterized by higher short-selling constraints should exhibit lower expected and future realized risk premia. To test this hypothesis, I use three proxies to capture short-selling constraints: Relative Short Interest (RSI) of Asquith et al. (2005), Estimated Shorting Fee (ESF) of Boehme et al. (2006), and Idiosyncratic Volatility ($IdioV$) under the physical measure of Wurgler and Zhuravskaya (2002).[1] The higher of these proxies typically indicate more severe short-selling constraints. The details of calculation of these variables are provided in the Appendix 3.9. In particular, I implement conditional double-sort analysis to test the above hypothesis. At the end of each month, I first sort all stocks into quintile portfolios based on each of the above proxies of short-selling constraint, and then I sort stocks in each of these quintile portfolios into quintile portfolios based on their FERP. This conditional sorting approach yields 25 portfolios. Besides, a set of high-minus-low spread portfolios are formed based independently on the FERP and on the proxy of short-selling constraint, respectively. I hold these portfolios over the next month and compute their equal-weighted risk premia.

Table 3.14 reports the average monthly realized risk premia of portfolios formed based on the above conditional double-sort technique. Regardless of the short-selling constraints proxy used, I find that the under-performance of the portfolio is driven by the stocks that are characterized by the most severe short-selling constraints. This pattern holds for all levels of the FERP. In particular,

information asymmetry in the stock and option markets. For example, classical microstructure models imply that information asymmetry affects prices and liquidity on financial markets (Kyle (1985) and Glosten and Milgrom (1985)). Empirical studies include Easley et al. (1998), Easley et al. (2002), Chung et al. (2005), Vega (2006), and more recently, Chung et al. (2010), Chen and Zhao (2012), and Chang and Lin (2015) propose to use alternative varieties of the static probability of informed trading as a measure of information asymmetry.

[1] The idiosyncratic volatility has also been shown by Shleifer and Vishny (1997) and Pontiff (2006) to deter arbitrage activity. In addition, Mendenhall (2004) and Cao and Han (2016) use idiosyncratic volatility to empirically measure arbitrage risk.

Panel A presents results based on the Relative Short Interest (RSI). For each level of the FERP, the risk premia of quintile portfolios with respect to the RSI decrease almost monotonically from portfolio 1 to 5. Moreover, the high-minus-low spread portfolios based on the RSI under different values of the FERP yield significant negative risk premia. Specifically, among the stocks with the lowest FERP, the RSI-based spread portfolio yields a risk premium of -0.73% per month (t-stat: -2.94), whereas it becomes -0.47% per month (t-stat: -2.01) for the stocks with the highest FERP. More importantly, for each level of the RSI, the high-minus-low spread portfolios with respect to the FERP still earn statistically significant positive risk premia. Furthermore, these risk premia tend to increase with respect to the RSI. For example, for the stocks that are classified in the quintile with the least severe short-selling constraints, the FERP-based high-minus-low spread portfolio yields a risk premium of 0.52% per month (t-stat: 2.50), while it increases to 0.77% per month (t-stat: 2.65) for the stocks in the quintile with the most severe short-selling constraints. When I use Estimated Shorting Fee (ESF) or Idiosyncratic Volatility under physical measure ($IdioV$) to proxy short-selling constraints in Panel B and Panel C, respectively, I find very similar results. The high-minus-low spread portfolios with respect to the short-selling constraint proxy earn significantly negative risk premia and the FERP-based high-minus-low spread portfolios yield statistically significant positive risk premia. Overall, Table 3.14 provides strong evidence to support the above hypothesis that stocks characterized by higher short-selling constraints are perceived negatively by informed investors and exhibit lower expected and future realized risk premia.

[Table 3.14 about here]

3.7.2.2 Short-Selling Constraints and Relative Trading Activity

The second necessary condition says that stocks characterized by high short-selling constraints would exhibit more active trading in its options than stocks. To test this hypothesis, I use the ratio of the trading volume in options to the trading volume in stocks as a proxy of relative trading activity. The higher the ratio is, the more active of the trading in options compared to the trading in stocks. Moreover, the ratio of the trading volume in options to the trading volume in stocks is also used as a measure of informed trades in the options market and it has been shown negatively related to the future stock returns (see Roll et al. (2010), Johnson and So (2012), among others). To be consistent with this hypothesis, I should observe the significantly positive relationship between the proxy of relative trading activity and the proxy of short-selling constraint. Figure 3.4 shows the dynamics of cross-sectional correlations between the proxy of relative trading activity and the proxy of short selling constraint. It is clear to see, regardless of the short selling constraints proxy used, that there is a positive relationship between the proxy of relative trading activity and the proxy of short selling constraint. In particular, the time-series average of the relationships between the proxy of relative trading activity and the proxy RSI, ESF, and $IdioV$ are 8.9%, 8.1%, and 13.4%, respectively.

[Figure 3.4 about here]

To further show that the above positive relationship is statistically significant, I implement the Fama-MacBeth cross-sectional regression of relative trading activity proxy on the proxy of short-selling constraint. I also introduce market beta ($BETA^P$) under physical measure, market value (MV), book-to-market ratio ($B2M$), and the illiquidity ($ILLIQ$) of Amihud (2002) as additional control variables in each regression. Table 3.15 shows the results from the cross-sectional regressions.

[Table 3.15 about here]

In Table 3.15, regardless of the short-selling constraints proxy used, the coefficient on the proxy of short-selling constraint is always positive and highly statistically significant. Moreover, the coefficient on the proxy of short-selling constraint becomes even larger after controlling for the above-mentioned control variables. For example, when I use RSI as the proxy of short-selling constraint in Panel A, the coefficients on RSI are 0.041 (t-stat: 12.11) and 0.146 (t-stat: 15.54) in the single-factor and multi-factor models, respectively. When I move to Panel B and Panel C, similar results are found, indicating that stocks characterized by higher short-selling constraints show more active trading in its options than its stocks.

3.7.2.3 Predictability of Filtered Expected Risk Premium and Liquidity

To be consistent with the prediction of Easley et al. (1998), the above third necessary condition implies that the filtered expected risk premium (FERP) would exhibit greater predictability when options are more liquid relative to the underlying stocks. To examine this hypothesis, I follow Cremers and Weinbaum (2010) and Huang and Li (2018) to construct the proxy to measure the relative liquidity of options to the stocks. In particular, to measure stock liquidity, I employ Amihud's illiquidity ratio (see Amihud (2002)), and to measure option liquidity, I use option volume as well as option open interest. I then construct two dummy variables to capture the relative liquidity of stock and option. Specifically, the first one is high option liquidity and low stock liquidity dummy, denoted as $HOLS$, and the other is low option liquidity and high stock liquidity dummy, denoted as $LOHS$. In particular, $HOLS$ is equal to one for stocks that belong to the top 33% of option liquidity and the bottom 33% of stock liquidity; similarly, $LOHS$ is equal to one for stocks that belong to the bottom 33% of option liquidity and the top 33% of stock liquidity. Then I run the cross-sectional regressions of stocks' risk premia on the lagged FERP and products of the FERP and the two dummy variables. I also introduce several frequently used variables such as market beta ($BETA^P$) under physical measure, market value (MV), book-to-market ratio ($B2M$), stock volume ($SVOLU$), short-term (1-month) risk-neutral volatility ($IVOL$), short-term risk-neutral skewness ($ISKEW$), and short-term risk-neutral kurtosis ($IKURT$) as additional control variables in regressions. Table 3.16 summarizes the results from the cross-sectional regressions.

[Table 3.16 about here]

It is clear to see that, in Table 3.16, no matter which option liquidity measure and whether to add additional control variables, the coefficient on the FERP is always positive and highly statistically significant. For example, in the left panel of Table 3.16, the magnitude of the coefficient on the FERP is 0.157 (t-stat: 2.98) without adding control variables. As a comparison, this coefficient becomes 0.165 (t-stat: 3.05) in the right panel of Table 3.16. More importantly, I find that the coefficient on the product of the FERP and $HOLS$ is always positive, whereas the coefficient on the product of the FERP and $LOHS$ is negative in the left panel, and positive in the right panel. Furthermore, the former coefficient is always larger than the latter one, and the F-test statistic reported in the bottom of Table 3.16 indicates that this difference is statistically significant. Overall, these results show that there is greater (smaller) predictive power of the FERP when option liquidity is high (low) relative to stock liquidity.

3.8 Conclusion

In the real world, markets are incomplete; hence options are no longer redundant assets, suggesting that option prices contain valuable information about underlying stock returns. This study contributes to the literature that focuses on using option-implied information to forecast underlying stock returns in two aspects. First, it exploits the information contained in the whole option price panels to estimate expected risk premia on individual stocks by building an empirical model to connect a large set of option-implied cumulants with expected stocks' risk premia through latent risk factors. Second, this paper proposes an easily implementable partial least squares-based method to filter future returns-related information embedded in the large set of risk-neutral cumulants. These ex-ante filtered expected risk premia (FERP) can be viewed as predictors of future stocks' risk premia. Moreover, this paper investigates the predictive ability of the ex-ante FERP to future stock returns cross-sectionally.

In terms of return predictability of the FERP, I find a significant positive relationship between the FERP and future realized stocks' risk premia during the period 1996-2017. Such positive relationship is robust to the short-term risk-neutral volatility, skewness and kurtosis that have been extensively studied and shown to related to future stocks' returns in the literature. What's more, the FERP continues positively related to future stocks' risk premia even after controlling for the first principal component of the second, third, or fourth-order risk-neutral cumulants. More importantly, these first principal components are unable to predict future stocks' risk premia, suggesting that the new estimation procedure proposed by this paper is more efficient in aggregating future returns-related information from a large set of risk-neutral cumulants than the principal component analysis technique. Besides, the Fama-MacBeth cross-sectional analysis also shows that the positive relationship between the FERP and future realized risk premium is remarkably robust even after taking various commonly used control variables into account. To quantify the magnitude of the FERP-based premium, I sort stocks according to their FERP in each month into decile portfolios and then calculate their post-ranking monthly risk premia. The FERP-based high-minus-low spread portfolio earns a risk premium of 0.89% per month (t-stat: 3.20), and the Fama-French-Carhart alpha of 1.06% per month (t-stat: 3.75).

Next, I show that the predictability of the FERP is consistent with the findings of Martin and Wagner (2018) who also show that the ex-ante expected excess return has a better out-of-sample performance in forecasting future stock returns than the traditional stock return predictors. Moreover, I find that the FERP on the FERP-based high-minus-low spread portfolio is highly correlated with the expected market risk premium of Martin (2017) and with the equal-weighted expected stocks' risk premium of Martin and Wagner (2018). In addition, I put forward a potential mechanism to explain the main finding that the FERP is positively significantly related to the future realized stock's risk premium. I assume that there are some informed investors in the market who perceive negatively on some stocks due to their private information. Those negatively perceived stocks are too costly or too risky to sell short due to short-selling constraints, and therefore the informed investors resort to the option market, leading option prices to provide information that leads stock price movements, which is consistent with the sequential trade model of Easley et al. (1998) as well as the noisy rational expectations model of An et al. (2014). For this conjectured mechanism to be valid, stocks characterized by higher short-selling constraints should be negatively perceived by informed investors, hence generating lower expected and future realized risk premia. Moreover, those highly short-sale constrained stocks would also exhibit more active trading in options compared to stocks given informed investors resort to the option market due to short-selling constraints. Besides, based on the sequential trade model of Easley et al. (1998), the predictive power of the FERP should be greater when options are more liquid relative to the underlying stocks. I empirically test these hypotheses by using three different proxies of short-selling constraint and the results in Section 3.7 confirm the above described hypotheses. I find that the under-performance portfolio is driven by the stocks that are classified in the more severe short-selling constraints groups. To summarize, the future return predictability of the ex-ante FERP can be potentially explained by informed trading driven by short-selling constraints.

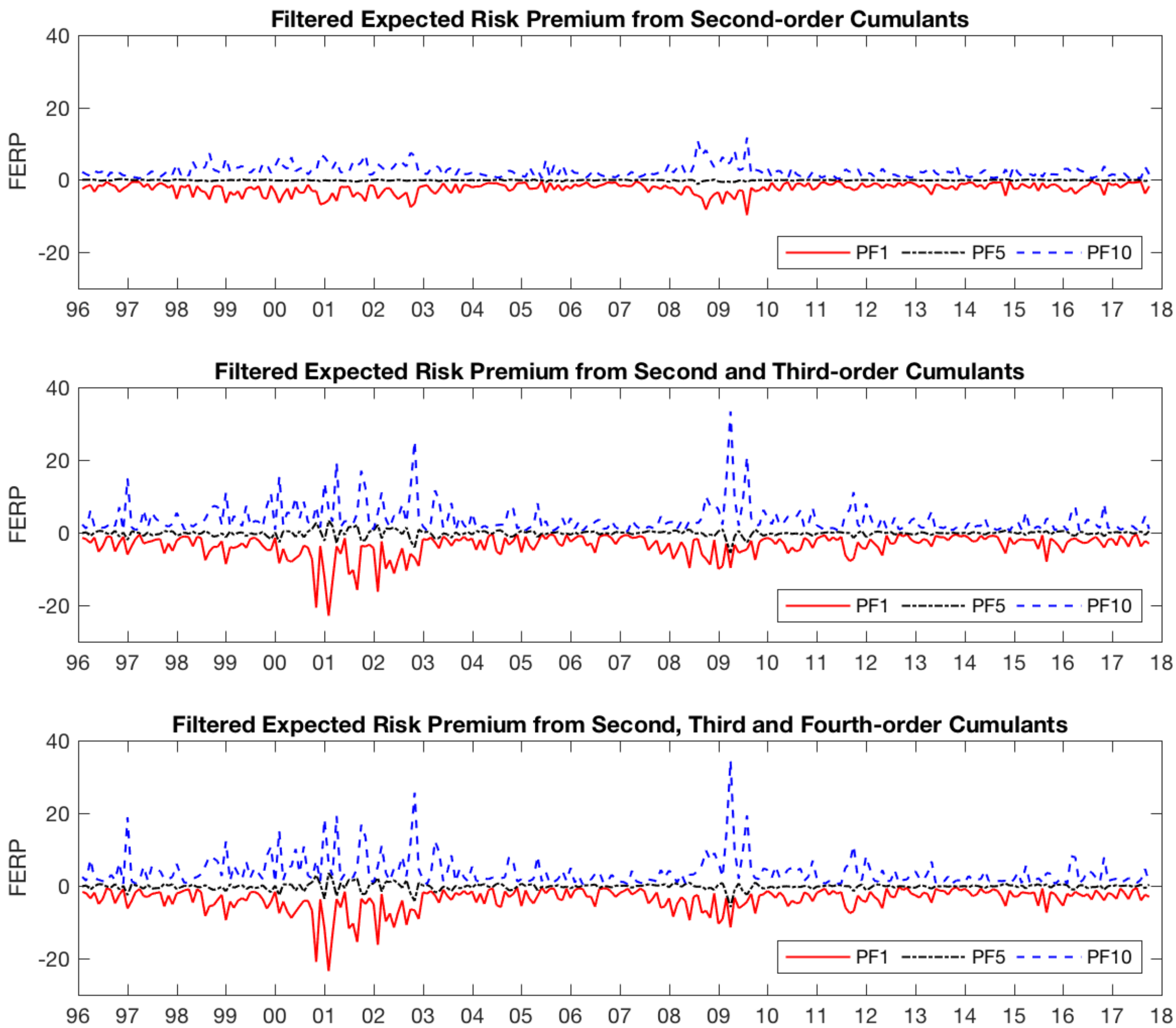
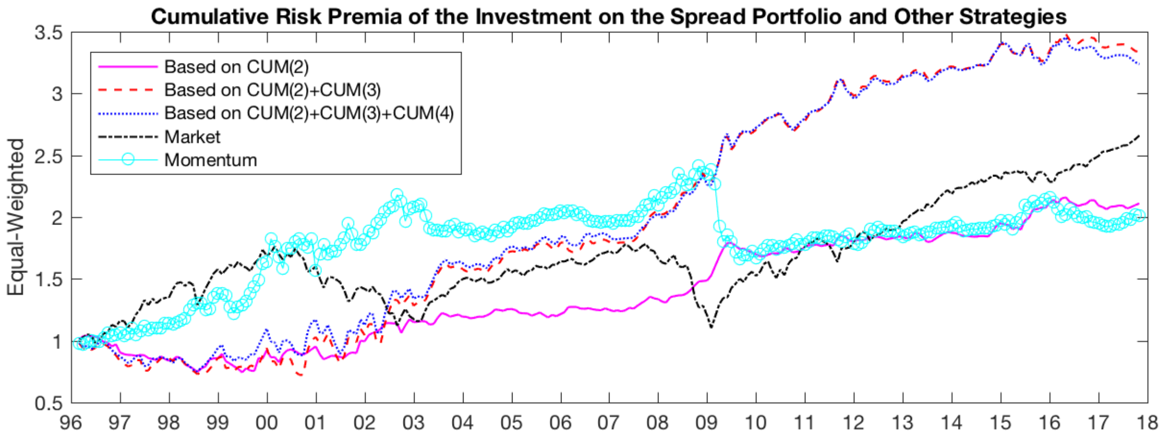


Figure 3.1: The dynamics of the monthly filtered expected risk premia (FERP) of the FERP-sorted portfolios: January 1996 - December 2017.



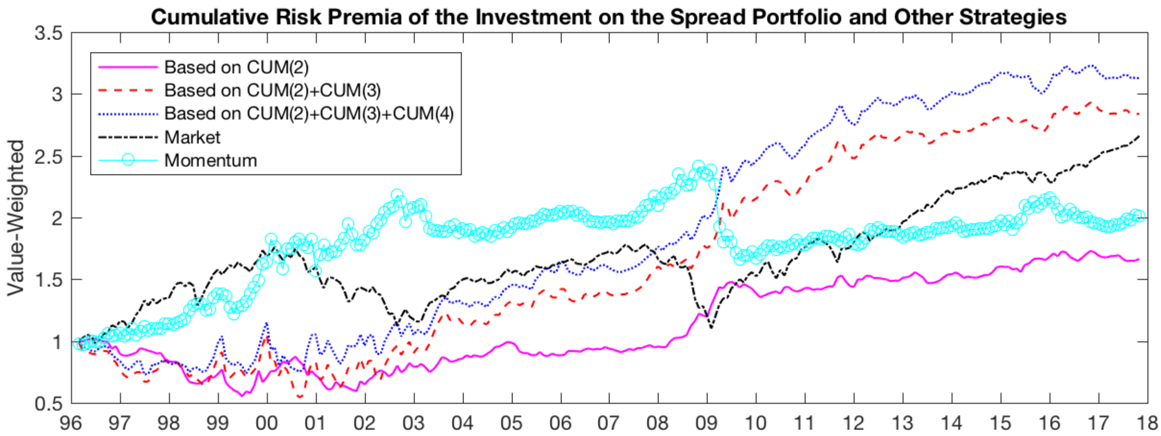


Figure 3.2: Cumulative risk premia of the investment on the spread portfolio, on the market, and on the momentum: January 1996 - December 2017.

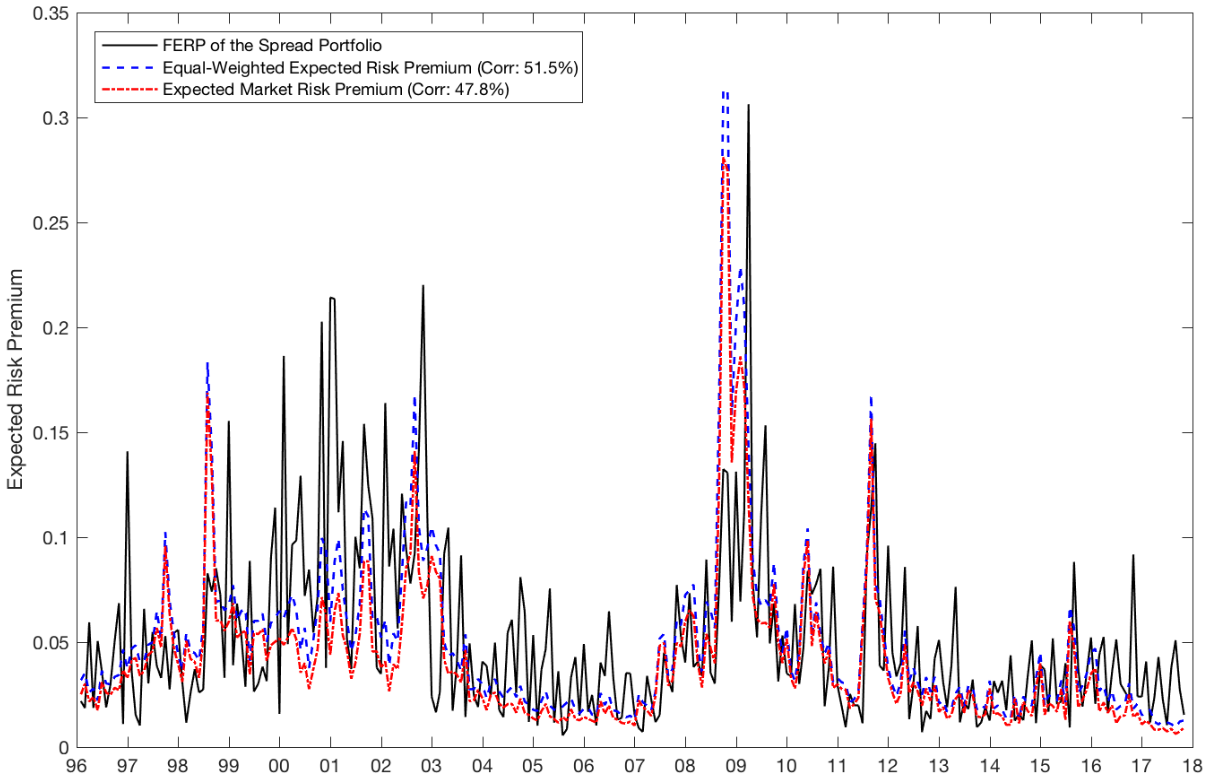


Figure 3.3: Filtered expected risk premium (FERP) and the calculated expected excess return of Martin and Wagner (2018): January 1996 - December 2017.

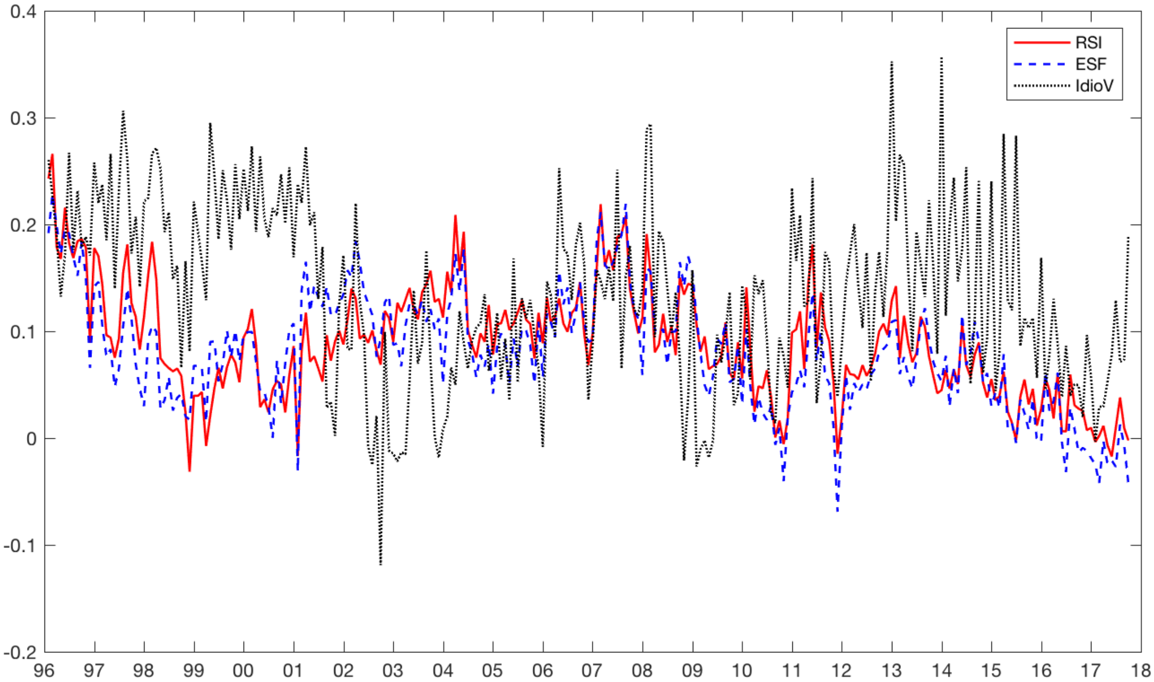


Figure 3.4: Cross-sectional correlations between proxies of relative trading activity and short-selling constraint: January 1996 - December 2017.

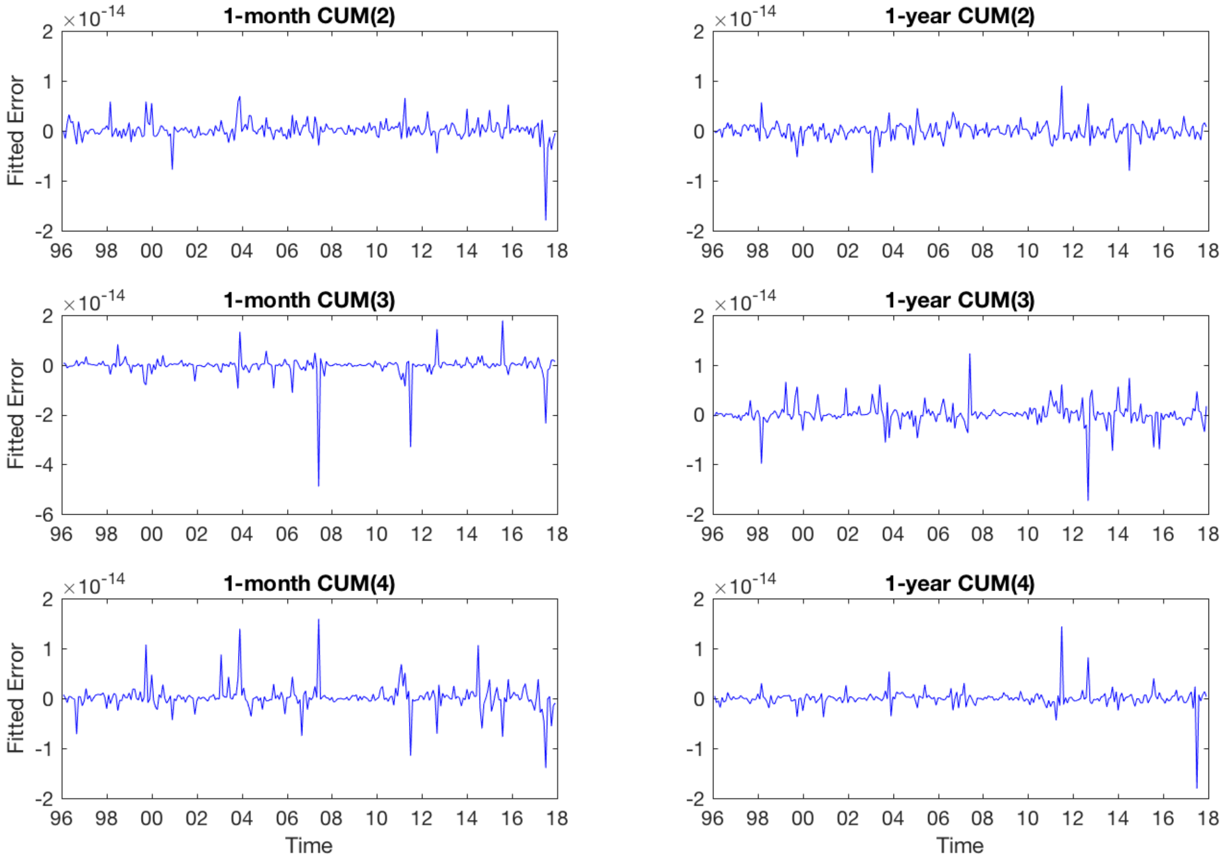


Figure 3.5: Average fitted errors for (demeaned) risk-neutral cumulants at different orders with maturities at 1 month and 1 year. CUM(n) stands for risk-neutral cumulant at the n-th order. Fitted error is defined as the difference between the data-implied demeaned risk-neutral cumulant (calculated by the model-free method of Bakshi et al. (2003)) and the model-implied risk-neutral cumulant (calculated as the product of filtered returns-related latent factors and factor loadings). Then I report the equal-weighted average of fitted errors across stocks for the period from January 1996 to December 2017.

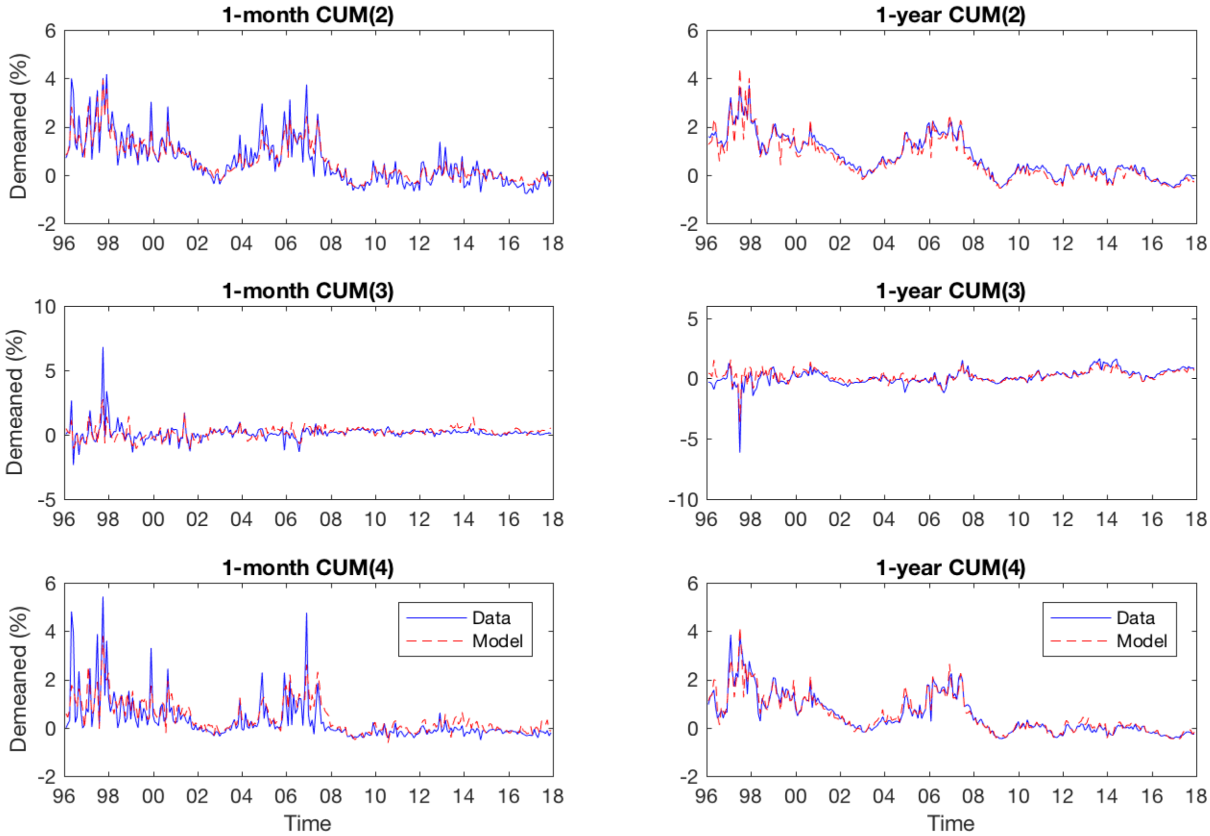


Figure 3.6: Model-implied and Data-implied risk-neutral cumulants at different orders with maturities at 1 month and 1 year for Apple Inc.: January 1996 - December 2017. CUM(n) stands for risk-neutral cumulant at the n-th order. Data-implied risk-neutral cumulant is calculated with the model-free method of Bakshi et al. (2003) and Model-implied risk-neutral cumulant is calculated as the product of filtered returns-related latent factors and factor loadings.

Table 3.1: Filtered Expected Risk Premium and Realized Portfolio Return

	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	10-1
Panel A: FERP based on Second-order Cumulants											
FERP	-2.359	-0.927	-0.567	-0.320	-0.111	0.090	0.299	0.549	0.922	2.427	4.786
EWRet	0.611	0.792	0.787	0.874	0.957	0.995	0.926	0.969	1.112	1.037	0.425
VWRet	1.329	1.095	0.925	1.096	1.128	1.199	1.151	1.274	1.340	1.583	0.254
Panel B: FERP based on Second and Third-order Cumulants											
FERP	-3.596	-1.628	-0.953	-0.514	-0.169	0.156	0.501	0.931	1.589	3.690	7.285
EWRet	0.263	0.630	0.801	0.894	1.025	0.970	1.091	1.106	1.125	1.157	0.894
VWRet	0.970	0.942	1.122	1.034	1.234	1.231	1.335	1.307	1.444	1.674	0.704
Panel C: FERP based on Second, Third and Fourth-order Cumulants											
FERP	-3.727	-1.705	-1.010	-0.551	-0.189	0.153	0.517	0.978	1.680	3.861	7.588
EWRet	0.253	0.603	0.796	0.916	1.032	0.998	1.135	1.105	1.115	1.110	0.857
VWRet	0.914	0.875	1.054	1.127	1.251	1.296	1.365	1.303	1.435	1.729	0.815

This table shows demeaned filtered expected risk premia (FERP) and related realized monthly excess returns (in %) of decile portfolios, which are constructed based on FERP. I sort all stocks on the basis of their FERP into deciles at the end of each month from January 1996 to December 2017. I then hold these decile portfolios over the next month and compute their equal-weighted (EWRet) and value-weighted (VWRet) monthly excess returns. A spread portfolio that goes long the portfolio with the highest FERP and short the portfolio with the lowest FERP is also formed. Panel A's summary statistics based on the FERP estimated from second-order cumulants, Panel B's results rely on the FERP estimated from second and third-order cumulants, and Panel C reports the summary statistics that built on the FERP estimated from second, third, and fourth-order cumulants.

Table 3.2: Summary Statistics of Filtered Expected Risk Premium-Sorted Decile Portfolios

	Panel A: Equal-weighted portfolios							Panel B: Value-weighted portfolios						
	FERP	EWRet	SD	Skew	Kurt	tval	Nobs	FERP	VWRet	SD	Skew	Kurt	tval	Nobs
PF1	-3.596	0.263	4.370	-0.800	6.256	0.707	46	-3.596	0.970	4.426	0.169	5.844	2.739	46
PF2	-1.628	0.630	3.385	-1.144	6.003	2.064	46	-1.628	0.942	3.478	-0.686	6.122	3.246	46
PF3	-0.953	0.801	2.939	-1.301	6.552	2.933	46	-0.953	1.122	3.062	-0.549	5.249	4.443	46
PF4	-0.514	0.894	2.717	-1.016	6.120	3.619	46	-0.514	1.034	2.672	-0.763	5.596	4.374	46
PF5	-0.169	1.025	2.615	-0.879	5.345	4.344	46	-0.169	1.234	2.727	-0.634	4.771	5.148	46
PF6	0.156	0.970	2.663	-0.658	4.856	4.079	46	0.156	1.231	2.718	-0.362	4.404	5.356	46
PF7	0.501	1.091	2.563	-0.313	4.127	4.886	46	0.501	1.335	2.675	-0.043	3.562	6.093	46
PF8	0.931	1.106	2.568	-0.018	4.199	4.996	46	0.931	1.307	2.618	0.412	3.793	5.841	46
PF9	1.589	1.125	2.849	0.149	5.271	4.809	46	1.589	1.444	2.972	0.358	4.696	6.029	46
PF10	3.690	1.157	3.977	0.162	7.093	3.471	46	3.690	1.674	4.013	0.368	7.524	5.118	46
10-1	7.285	0.894	4.542	0.313	5.134	3.200	-	7.285	0.704	5.136	-0.523	5.931	2.373	-

This table shows the descriptive statistics of decile portfolios, which are constructed based on filtered expected risk premia (FERP). I sort all stocks on the basis of their FERP into deciles at the end of each month from January 1996 to December 2017. I then hold these decile portfolios over the next month and compute their equal-weighted (Panel A) and value-weighted (Panel B) monthly excess returns (in %). A spread portfolio that goes long the Portfolio 10 and short the Portfolio 1 is also formed. Columns under FERP, EWRet (VWRet), SD, Skew, and Kurt report sample average of filtered expected risk premium, sample average of realized equal-weighted risk premium (value-weighted risk premium), standard deviation, skewness, and kurtosis. The column labeled with tval presents t-values for testing the average realized risk premium of each portfolio is 0, which are calculated using Newey-West standard errors with four lags. The number of stocks in each portfolio is reported in the last column of each panel (Nobs).

Table 3.3: Characteristics of Filtered Expected Risk Premium-Sorted Decile Portfolios

	FERP	EWRet	MV	B2M	MOM	$BETA^P$	$BETA^Q$	ILLIQ	SVOLU	REV	MAX	MIN	ZS	OVOLU	OI	P2AR
PF1	-3.596	0.263	23.407	0.513	8.916	1.164	1.175	1.496	112.902	0.735	5.295	-4.707	-0.813	182.225	194.717	0.440
PF2	-1.628	0.630	23.773	0.448	11.033	1.054	1.098	1.516	95.322	1.078	4.493	-4.075	-0.993	164.736	170.782	0.427
PF3	-0.953	0.801	23.856	0.437	12.371	0.988	1.065	1.529	83.345	1.120	4.114	-3.777	-1.032	151.831	158.518	0.429
PF4	-0.514	0.894	23.882	0.429	12.747	0.967	1.060	1.523	82.842	1.230	3.998	-3.590	-1.035	147.994	161.363	0.429
PF5	-0.169	1.025	23.970	0.420	13.130	0.963	1.057	1.503	85.323	1.228	3.896	-3.544	-1.002	162.357	169.366	0.428
PF6	0.156	0.970	23.968	0.419	12.888	0.953	1.054	1.523	82.697	1.096	3.841	-3.544	-1.004	152.842	164.195	0.432
PF7	0.501	1.091	23.912	0.421	13.061	0.962	1.048	1.552	81.254	1.170	3.862	-3.569	-1.019	146.619	156.868	0.430
PF8	0.931	1.106	23.892	0.429	12.874	0.966	1.063	1.578	81.834	1.028	3.950	-3.650	-1.019	146.817	159.329	0.429
PF9	1.589	1.125	23.796	0.437	12.726	0.992	1.061	1.500	92.761	0.945	4.180	-3.864	-0.998	156.379	164.469	0.422
PF10	3.690	1.157	23.432	0.498	10.204	1.094	1.148	0.953	111.320	0.630	5.089	-4.572	-0.803	172.678	179.462	0.423
10-1	7.285***	0.894***	0.024	-0.015	1.288	-0.070	-0.027	-0.543	-1.582	-0.104	-0.206	0.135	0.010	-9.547	-15.255	−0.017***
t(10-1)	(12.595)	(3.200)	(0.363)	(-0.790)	(0.669)	(-1.043)	(-0.310)	(-1.058)	(-0.173)	(-0.252)	(-0.726)	(0.559)	(0.236)	(-0.649)	(-1.136)	(-3.360)

This table shows the average characteristics of decile portfolios that are constructed based on the ex-ante filtered expected risk premia (FERP). At the end of each month, stocks are sorted into decile portfolios based on their FERP. Portfolio 1 contains the stocks with the lowest FERP while Portfolio 10 includes the highest ones. The data sample covers the period from January 1996 to December 2017. EWRet stands for firms' monthly realized risk premium. MV stands for firms' market value (in log). B2M stands for firms' book-to-market value ratio. MOM stands for firms' momentum. $BETA^P$ ($BETA^Q$) stands for firms' market beta under physical (risk-neutral) measure. ILLIQ stands for the price impact ratio of Amihud (2002), multiplied by 10^8. SVOLU stands for firms' stock trading volume (in millions). REV denotes firms' short-term reversal, computed as firms' excess return in the previous month. MAX (MIN) denotes the maximum (minimum) daily stocks' excess return over the previous month. ZS stands for firm's default risk, computed as the Z-score of Zmijewski (1984). OVOLU denotes the total number of traded contracts (in thousands) that are used to calculate risk-neutral cumulants. OI denotes the average number of outstanding contracts (in thousands) of the options that are used to calculate risk-neutral cumulants. P2AR stands for put-to-all options volume ratio, computed as the ratio of the total volume across all put options divided by the total volume across all put and call options. The second last row shows the difference between the portfolio with the highest FERP and the portfolio with lowest FERP in each case. The last row reports t-values, calculated using Newey-West standard errors with four lags. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 3.4: Risk-Adjusted Portfolio Returns

	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	10-1
Panel A: The CAPM Model											
Alpha	-0.077	0.358	0.551	0.666	0.792	0.751	0.877	0.895	0.897	0.878	0.955
	(-0.274)	(1.456)	(2.553)	(3.420)	(4.276)	(3.998)	(5.343)	(5.463)	(5.294)	(3.512)	(3.331)
MKT	0.535	0.427	0.393	0.360	0.366	0.345	0.337	0.333	0.358	0.439	-0.096
	(7.563)	(6.616)	(7.505)	(8.177)	(8.796)	(7.253)	(9.700)	(9.758)	(9.099)	(8.019)	(-1.153)
Panel B: The Fama-French Three-Factor Model											
Alpha	-0.136	0.296	0.497	0.611	0.735	0.684	0.822	0.847	0.841	0.824	0.959
	(-0.499)	(1.327)	(2.523)	(3.708)	(4.777)	(4.384)	(5.792)	(5.967)	(5.579)	(3.448)	(3.413)
MKT	0.532	0.437	0.394	0.378	0.376	0.367	0.353	0.347	0.372	0.438	-0.094
	(7.224)	(7.241)	(7.912)	(9.569)	(10.909)	(10.416)	(13.508)	(13.098)	(12.354)	(8.593)	(-1.106)
SMB	0.126	0.075	0.101	0.018	0.063	0.021	0.028	0.020	0.039	0.106	-0.020
	(1.709)	(1.559)	(2.360)	(0.466)	(2.000)	(0.522)	(0.734)	(0.500)	(0.907)	(1.522)	(-0.205)
HML	0.158	0.196	0.153	0.195	0.181	0.238	0.190	0.168	0.187	0.151	-0.007
	(1.957)	(2.921)	(2.676)	(3.569)	(3.259)	(4.684)	(4.568)	(3.824)	(3.839)	(2.127)	(-0.062)
Panel C: The Carhart Four-Factor Model											
Alpha	-0.169	0.253	0.450	0.572	0.697	0.668	0.798	0.854	0.860	0.889	1.057
	(-0.626)	(1.111)	(2.205)	(3.366)	(4.406)	(4.187)	(5.425)	(5.775)	(5.337)	(3.556)	(3.748)
MKT	0.551	0.462	0.421	0.400	0.398	0.376	0.367	0.343	0.361	0.401	-0.150
	(7.727)	(7.588)	(8.230)	(10.127)	(11.122)	(9.516)	(12.193)	(11.360)	(10.589)	(8.321)	(-1.918)
SMB	0.120	0.067	0.092	0.010	0.056	0.018	0.023	0.022	0.043	0.118	-0.002
	(1.619)	(1.422)	(2.198)	(0.258)	(1.765)	(0.449)	(0.600)	(0.555)	(1.051)	(1.880)	(-0.023)
HML	0.177	0.221	0.180	0.217	0.203	0.247	0.204	0.164	0.177	0.113	-0.064
	(2.213)	(3.320)	(3.347)	(4.628)	(4.144)	(5.092)	(5.159)	(3.496)	(3.165)	(1.352)	(-0.514)
MOM	0.048	0.062	0.068	0.056	0.055	0.024	0.035	-0.010	-0.027	-0.093	-0.141
	(0.888)	(1.444)	(1.644)	(1.455)	(1.835)	(0.707)	(1.099)	(-0.312)	(-0.662)	(-1.792)	(-1.949)
Panel D: The Fama-French Five-Factor Model											
Alpha	-0.045	0.311	0.479	0.537	0.642	0.582	0.728	0.776	0.780	0.831	0.876
	(-0.172)	(1.459)	(2.482)	(3.455)	(4.478)	(3.932)	(5.129)	(5.458)	(5.020)	(3.380)	(3.050)
MKT	0.494	0.430	0.403	0.414	0.421	0.414	0.397	0.381	0.404	0.436	-0.058
	(6.840)	(6.978)	(7.912)	(10.200)	(13.071)	(11.896)	(13.408)	(12.412)	(12.949)	(7.955)	(-0.833)
SMB	0.045	0.063	0.106	0.050	0.112	0.086	0.083	0.062	0.062	0.096	0.051
	(0.454)	(1.004)	(2.026)	(1.095)	(2.652)	(2.052)	(1.990)	(1.459)	(1.327)	(1.166)	(0.419)
HML	0.193	0.205	0.133	0.127	0.104	0.168	0.120	0.115	0.126	0.150	-0.043
	(1.795)	(2.186)	(1.455)	(1.686)	(1.470)	(2.532)	(2.276)	(2.258)	(2.113)	(1.455)	(-0.323)
RMW	-0.208	-0.031	0.021	0.109	0.152	0.188	0.164	0.123	0.084	-0.022	0.186
	(-1.859)	(-0.390)	(0.278)	(1.745)	(2.349)	(3.169)	(2.597)	(1.821)	(1.277)	(-0.200)	(1.165)
CMA	0.081	0.003	0.030	0.077	0.064	0.019	0.039	0.030	0.081	0.019	-0.062
	(0.503)	(0.029)	(0.273)	(0.862)	(0.737)	(0.247)	(0.508)	(0.360)	(1.020)	(0.136)	(-0.323)
Panel E: The VRP-Factor Model											
Alpha	-0.356	0.007	0.216	0.463	0.568	0.533	0.752	0.748	0.851	0.718	1.074
	(-1.122)	(0.021)	(0.662)	(1.578)	(2.184)	(2.128)	(3.636)	(4.000)	(5.026)	(2.661)	(3.504)
MKT	0.513	0.412	0.370	0.365	0.361	0.354	0.347	0.339	0.373	0.429	-0.084
	(6.913)	(7.676)	(9.271)	(10.471)	(12.621)	(12.591)	(13.605)	(12.747)	(12.443)	(8.430)	(-0.999)
SMB	0.125	0.074	0.100	0.017	0.063	0.020	0.027	0.020	0.039	0.105	-0.020
	(1.707)	(1.543)	(2.349)	(0.440)	(1.958)	(0.496)	(0.713)	(0.480)	(0.908)	(1.495)	(-0.202)
HML	0.152	0.188	0.145	0.191	0.176	0.234	0.188	0.165	0.188	0.148	-0.004
	(1.920)	(2.988)	(2.778)	(3.640)	(3.324)	(4.780)	(4.520)	(3.820)	(3.824)	(2.132)	(-0.035)
VRP	0.014	0.019	0.018	0.010	0.011	0.010	0.005	0.006	-0.001	0.007	-0.007
	(1.201)	(1.384)	(1.339)	(0.762)	(0.962)	(0.937)	(0.492)	(0.782)	(-0.095)	(0.682)	(-0.762)
Panel F: The Mispricing-Factor Model											
Alpha	-0.170	0.205	0.415	0.480	0.610	0.576	0.734	0.816	0.888	0.955	1.125
	(-0.604)	(0.846)	(1.926)	(2.680)	(3.687)	(3.274)	(4.548)	(4.928)	(4.732)	(3.395)	(3.688)
MKT	0.516	0.467	0.425	0.427	0.422	0.409	0.389	0.369	0.378	0.402	-0.114
	(6.771)	(7.805)	(8.481)	(10.921)	(11.992)	(10.078)	(12.091)	(11.395)	(10.239)	(7.536)	(-1.651)
SMB	0.141	0.080	0.104	0.026	0.067	0.028	0.033	0.014	0.010	0.061	-0.080
	(1.655)	(1.238)	(1.913)	(0.443)	(1.495)	(0.429)	(0.580)	(0.230)	(0.162)	(0.707)	(-0.704)
MGMT	0.108	0.162	0.132	0.193	0.173	0.219	0.184	0.145	0.144	0.096	-0.012
	(1.138)	(1.920)	(2.038)	(3.066)	(2.852)	(3.136)	(2.929)	(2.184)	(1.887)	(1.016)	(-0.083)
PERF	-0.060	0.001	0.009	0.023	0.022	0.000	-0.002	-0.014	-0.049	-0.117	-0.058
	(-1.071)	(0.031)	(0.218)	(0.617)	(0.703)	(0.012)	(-0.049)	(-0.431)	(-1.110)	(-2.180)	(-0.708)

This table reports alphas and factor loadings of regressing realized risk premia of the ex-ante filtered expected risk premium-sorted decile portfolios on the market factor (CAPM), on the Fama-French three factors (Fama and French (1993)), on the Momentum factor (Carhart (1997)), on the Fama-French five factors (Fama and French (2016)), on the variance risk premia (VRP) factor, and on the mispricing factors $MGMT$ and $PERF$ (Stambaugh and Yuan (2016)), respectively. The Newey-West t-statistics with four lags are reported in parentheses. Data sample covers the period from January 1996 through December 2017.

Table 3.5: FERP and Risk-Neutral Volatility

		Risk-Neutral Volatility					
		IV1	IV2	IV3	IV4	IV5	5-1
Filtered Expected Risk Premium	FERP1	0.788	0.561	0.621	0.419	-0.153	-0.942
		(3.257)	(1.922)	(1.781)	(1.117)	(-0.321)	(-2.915)
	FERP2	1.011	0.918	0.915	0.743	0.651	-0.359
		(4.661)	(3.904)	(3.596)	(2.556)	(1.922)	(-1.858)
	FERP3	1.133	1.018	1.064	0.921	0.853	-0.280
		(6.000)	(4.646)	(4.390)	(3.649)	(2.757)	(-1.636)
	FERP4	1.188	1.187	1.171	1.132	0.806	-0.382
		(6.552)	(5.342)	(5.333)	(4.754)	(2.727)	(-1.998)
	FERP5	1.366	1.218	1.114	1.181	0.838	-0.528
		(7.258)	(5.246)	(4.152)	(3.388)	(1.992)	(-1.834)
	5-1	0.577	0.657	0.493	0.762	0.992	-
		(2.959)	(3.078)	(1.925)	(2.635)	(2.960)	-

This table reports average realized monthly risk premia (in %) of double-sort portfolios. At the end of each month, stocks are sorted into quintile portfolios based independently on the filtered expected risk premium (FERP) and on the risk-neutral volatility, respectively. I then form 25 portfolios based on the intersection of the two types of portfolios, and these portfolios are held over the next month and their average monthly equal-weighted risk premia are reported. The high-minus-low spread portfolios' risk premia based on the FERP and on the risk-neutral volatility are also presented in the last row and column, respectively. The Newey-West t-statistics with four lags are presented in parentheses. Data sample covers the period from January 1996 to December 2017.

Table 3.6: FERP and Risk-Neutral Skewness

		Risk-Neutral Skewness					
		IS1	IS2	IS3	IS4	IS5	5-1
Filtered Expected Risk Premium	FERP1	0.580	0.608	0.520	0.506	0.018	-0.561
		(1.929)	(1.850)	(1.487)	(1.392)	(0.048)	(-2.687)
	FERP2	1.015	1.020	0.953	0.802	0.451	-0.565
		(4.141)	(4.171)	(3.691)	(2.834)	(1.489)	(-4.015)
	FERP3	1.195	1.078	1.036	1.072	0.608	-0.587
		(5.709)	(4.617)	(4.335)	(4.058)	(2.245)	(-5.240)
	FERP4	1.286	1.182	1.128	1.114	0.776	-0.510
		(6.348)	(5.368)	(4.950)	(4.492)	(2.956)	(-3.032)
	FERP5	1.317	1.303	1.209	1.151	0.731	-0.585
		(5.431)	(4.939)	(4.068)	(3.696)	(2.133)	(-3.325)
	5-1	0.737	0.695	0.688	0.645	0.713	-
		(3.534)	(2.773)	(2.716)	(2.366)	(2.887)	-

This table reports average realized monthly risk premia (in %) of double-sort portfolios. At the end of each month, stocks are sorted into quintile portfolios based independently on the filtered expected risk premium (FERP) and on the risk-neutral skewness, respectively. I then form 25 portfolios based on the intersection of the two types of portfolios, and these portfolios are held over the next month and their average monthly equal-weighted risk premia are reported. The high-minus-low spread portfolios' risk premia based on the FERP and on the risk-neutral skewness are also presented in the last row and column, respectively. The Newey-West t-statistics with four lags are presented in parentheses. Data sample covers the period from January 1996 to December 2017.

Table 3.7: FERP and Risk-Neutral Kurtosis

		Risk-Neutral Kurtosis					
		IK1	IK2	IK3	IK4	IK5	5-1
Filtered Expected Risk Premium	FERP1	0.456	0.576	0.516	0.289	0.407	-0.049
		(1.191)	(1.477)	(1.494)	(0.879)	(1.466)	(-0.215)
	FERP2	0.954	1.013	0.781	0.798	0.697	-0.257
		(3.124)	(3.884)	(3.028)	(3.122)	(2.657)	(-1.580)
	FERP3	1.063	1.060	1.036	1.020	0.809	-0.254
		(3.845)	(4.294)	(4.568)	(4.291)	(3.502)	(-1.849)
	FERP4	1.199	1.231	1.092	0.938	1.025	-0.173
		(5.204)	(4.982)	(4.948)	(4.050)	(4.540)	(-1.127)
	FERP5	1.222	1.203	1.203	1.070	1.015	-0.207
		(3.331)	(3.734)	(4.325)	(4.157)	(4.239)	(-0.972)
	5-1	0.767	0.627	0.687	0.780	0.609	-
		(2.852)	(2.124)	(2.665)	(3.161)	(3.299)	-

This table reports average realized monthly risk premia (in %) of double-sort portfolios. At the end of each month, stocks are sorted into quintile portfolios based independently on the filtered expected risk premium (FERP) and on the risk-neutral kurtosis, respectively. I then form 25 portfolios based on the intersection of the two types of portfolios, and these portfolios are held over the next month and their monthly equal-weighted risk premia are reported. The high-minus-low spread portfolios' risk premia based on the FERP and on the risk-neutral kurtosis are also presented in the last row and column, respectively. The Newey-West t-statistics with four lags are presented in parentheses. Data sample covers the period from January 1996 to December 2017.

Table 3.8: Filtered Expected Risk Premium and the First Principle Component of Risk-Neutral Cumulants

	Panel A: The First PC of Second-order Cumulants						Panel B: The First PC of Third-order Cumulants						Panel C: The First PC of Fourth-order Cumulants					
	PCA-1	PCA-2	PCA-3	PCA-4	PCA-5	5-1	PCA-1	PCA-2	PCA-3	PCA-4	PCA-5	5-1	PCA-1	PCA-2	PCA-3	PCA-4	PCA-5	5-1
FERP1	0.733	0.580	0.538	0.551	-0.158	-0.891	0.400	0.717	0.542	0.560	0.022	-0.378	0.686	0.661	0.476	0.493	-0.074	-0.760
	(3.044)	(1.973)	(1.532)	(1.439)	(-0.336)	(-2.735)	(1.195)	(2.379)	(1.645)	(1.527)	(0.051)	(-1.383)	(2.773)	(2.270)	(1.397)	(1.279)	(-0.157)	(-2.409)
FERP2	0.948	0.914	0.916	0.739	0.722	-0.226	1.025	0.938	0.811	0.893	0.572	-0.454	0.908	0.892	0.858	0.782	0.798	-0.109
	(4.504)	(3.785)	(3.616)	(2.498)	(2.131)	(-1.101)	(3.979)	(3.757)	(2.981)	(3.539)	(1.871)	(-3.252)	(4.356)	(3.567)	(3.352)	(2.737)	(2.352)	(-0.525)
FERP3	1.089	1.064	0.953	1.037	0.843	-0.246	1.100	1.050	1.043	1.028	0.765	-0.335	1.044	1.007	1.053	1.023	0.863	-0.181
	(5.667)	(4.954)	(4.035)	(4.042)	(2.678)	(-1.416)	(4.605)	(4.588)	(4.279)	(4.175)	(2.972)	(-2.512)	(5.431)	(4.547)	(4.428)	(3.948)	(2.820)	(-1.044)
FERP4	1.171	1.178	1.208	1.006	0.924	-0.248	1.041	1.149	1.022	1.153	1.119	0.078	1.128	1.121	1.289	1.013	0.936	-0.192
	(6.387)	(5.447)	(5.470)	(4.079)	(3.108)	(-1.228)	(4.863)	(5.107)	(4.537)	(5.008)	(4.274)	(0.510)	(6.059)	(5.414)	(5.667)	(4.088)	(3.213)	(-0.985)
FERP5	1.320	1.194	1.147	1.158	0.895	-0.425	1.186	1.017	1.205	1.224	1.077	-0.109	1.319	1.158	1.099	1.148	0.992	-0.326
	(7.191)	(5.194)	(4.464)	(3.209)	(2.081)	(-1.375)	(4.524)	(3.831)	(4.796)	(3.852)	(2.826)	(-0.433)	(6.990)	(5.085)	(4.062)	(3.320)	(2.319)	(-1.060)
5-1	0.587	0.614	0.610	0.608	1.052	-	0.786	0.300	0.663	0.664	1.055	-	0.632	0.498	0.624	0.655	1.066	-
	(3.050)	(2.845)	(2.359)	(2.082)	(3.192)	-	(3.387)	(1.277)	(2.899)	(2.166)	(3.564)	-	(3.194)	(2.230)	(2.560)	(2.261)	(3.257)	-

This table reports average monthly realized risk premia (in %) of double-sort portfolios. At the end of each month, stocks are sorted into quintile portfolios based independently on the filtered expected risk premium (FERP) and on the first principal component of second (Panel A), third (Panel B), and fourth-order cumulants (Panel C), respectively. I then form 25 portfolios based on the intersection of the two types of portfolios, and these portfolios are held over the next month and their monthly equal-weighted risk premia are reported. The high-minus-low spread portfolios' risk premia based on the FERP and on different first principal components are also presented. The Newey-West t-statistics with four lags are presented in parentheses. Data sample covers the period from January 1996 to December 2017.

Table 3.9: Filtered Expected Risk Premium and Fama-MacBeth Regressions

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13
Intercept	0.979	0.710	-0.176	0.672	0.925	0.481	-0.340	0.575	0.222	0.424	2.650	1.314	3.632
	(4.951)	(0.781)	(-0.162)	(0.719)	(0.805)	(0.554)	(-0.393)	(0.635)	(0.220)	(0.407)	(2.675)	(1.504)	(3.278)
FERP	0.128***	0.080**	0.080***	0.082***	0.084***	0.090***	0.085***	0.078**	0.073**	0.075**	0.079**	0.065**	0.080***
	(3.168)	(2.262)	(2.423)	(2.341)	(2.410)	(2.726)	(2.517)	(2.238)	(2.096)	(2.144)	(2.164)	(2.075)	(2.776)
$BETA^Q$	-	0.111	0.105	0.102	0.107	0.103	0.088	0.113	0.108	0.107	0.129	0.089	-0.009
	-	(3.231)	(3.251)	(2.997)	(3.098)	(3.230)	(2.534)	(3.373)	(3.222)	(3.182)	(3.675)	(1.860)	(-0.192)
MV	-	-0.015	0.023	-0.018	-0.026	-0.010	0.008	-0.016	0.003	-0.006	-0.067	-0.033	-0.088
	-	(-0.413)	(0.533)	(-0.486)	(-0.593)	(-0.288)	(0.250)	(-0.458)	(0.083)	(-0.137)	(-1.803)	(-0.954)	(-2.031)
MOM	-	0.038	0.037	0.043	0.038	0.039	0.040	0.038	0.038	0.038	0.038	0.038	0.043
	-	(19.048)	(18.729)	(20.559)	(18.948)	(19.815)	(20.877)	(19.407)	(18.982)	(19.049)	(19.540)	(19.883)	(23.713)
B2M	-	0.087	0.082	0.094	0.085	0.072	0.102	0.095	0.078	0.073	0.099	0.064	0.062
	-	(0.843)	(0.828)	(0.908)	(0.836)	(0.694)	(0.989)	(0.933)	(0.775)	(0.730)	(0.970)	(0.665)	(0.693)
SVOLU	-	-	-0.075	-	-	-	-	-	-	-	-	-	-0.258
	-	-	(-2.088)	-	-	-	-	-	-	-	-	-	(-3.556)
REV	-	-	-	-0.049	-	-	-	-	-	-	-	-	-0.060
	-	-	-	(-14.413)	-	-	-	-	-	-	-	-	(-13.403)
ILLIQ	-	-	-	-	-0.032	-	-	-	-	-	-	-	-0.023
	-	-	-	-	(-0.872)	-	-	-	-	-	-	-	(-0.723)
MAX	-	-	-	-	-	0.003	-	-	-	-	-	-	0.098
	-	-	-	-	-	(0.162)	-	-	-	-	-	-	(7.241)
MIN	-	-	-	-	-	-	-0.106	-	-	-	-	-	-0.036
	-	-	-	-	-	-	(-6.801)	-	-	-	-	-	(-3.007)
ZS	-	-	-	-	-	-	-	-0.061	-	-	-	-	-0.086
	-	-	-	-	-	-	-	(-2.255)	-	-	-	-	(-3.531)
OVOLU	-	-	-	-	-	-	-	-	-0.176	-	-	-	0.235
	-	-	-	-	-	-	-	-	(-0.972)	-	-	-	(0.834)
OI	-	-	-	-	-	-	-	-	-	-0.117	-	-	0.560
	-	-	-	-	-	-	-	-	-	(-0.744)	-	-	(2.036)
P2AR	-	-	-	-	-	-	-	-	-	-	-1.610	-	-1.669
	-	-	-	-	-	-	-	-	-	-	(-6.637)	-	(-8.744)
IVOL	-	-	-	-	-	-	-	-	-	-	-	-0.525	-3.925
	-	-	-	-	-	-	-	-	-	-	-	(-0.435)	(-3.425)
ISKEW	-	-	-	-	-	-	-	-	-	-	-	-0.704	-2.013
	-	-	-	-	-	-	-	-	-	-	-	(-1.124)	(-3.335)
IKURT	-	-	-	-	-	-	-	-	-	-	-	-0.354	0.110
	-	-	-	-	-	-	-	-	-	-	-	(-1.170)	(0.367)
$Adj-R^2$	0.048	0.155	0.165	0.173	0.161	0.165	0.169	0.165	0.163	0.163	0.163	0.190	0.248
	(10.776)	(20.916)	(22.080)	(23.486)	(21.962)	(22.049)	(22.810)	(21.546)	(21.716)	(21.608)	(21.734)	(23.921)	(30.641)

This table reports the Fama-MacBeth coefficients of cross-sectional regressions of monthly realized risk premia on lagged ex-ante filtered expected risk premium (FERP) and a set of frequently used firm characteristics in the literature. The FERP is estimated based on the second and third-order risk-neutral cumulants with the PLS-based procedures introduced in the main body. Model 1 (M1) only consider FERP. Firms' risk-neutral beta ($BETA^Q$), market value (MV), momentum (MOM), and book-to-market ratio ($B2M$) are controlled in Models 2-13 (M2-M13). Model 3 additionally controls for stock trading volume ($SVOLU$). Model 4 additionally controls for 1-month reversal (REV). Model 5 controls for stock illiquidity proxied by Amihud's (2002) price impact ratio ($ILLIQ$). Model 6 and 7 additionally control for the maximum (MAX) and minimum (MIN) daily returns over the previous month, respectively. Model 8 additionally controls for firms' default risk (ZS). Model 9 and 10 additionally control for the trading volume of options used to compute risk-neutral cumulants ($OVOLU$) and options open interest (OI), respectively. Model 11 additionally controls for put-to-all options volume ratio ($P2AR$). Model 12 additionally control for 30-day maturity risk-neutral volatility ($IVOL$), risk-neutral skewness ($ISKEW$), and risk-neutral kurtosis ($IKURT$). Finally, Model 13 considers all the above mentioned variables. The second last row presents adjusted R^2. Data sample covers the period from January 1996 to December 2017. The Newey-West t-statistics with four lags are provided in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 3.10: Long-Term Performance of Filtered Expected Risk Premium-Sorted Portfolios

Horizon	$t+1$			$t+2$			$t+3$			$t+6$			$t+12$		
	Ret	α_{FF3}	α_{FFC}	Ret	α_{FF3}	α_{FFC}	Ret	α_{FF3}	α_{FFC}	Ret	α_{FF3}	α_{FFC}	Ret	α_{FF3}	α_{FFC}
PF1	0.263	-0.136	-0.169	0.780	0.211	0.302	0.845	0.515	0.578	0.843	0.685	0.743	0.924	0.874	0.905
PF2	0.630	0.296	0.253	0.810	0.347	0.404	0.815	0.549	0.598	0.839	0.719	0.769	0.867	0.829	0.860
PF3	0.801	0.497	0.450	0.919	0.524	0.568	0.930	0.702	0.744	0.940	0.838	0.873	0.945	0.914	0.939
PF4	0.894	0.611	0.572	1.001	0.620	0.668	1.009	0.792	0.829	0.974	0.870	0.907	0.977	0.939	0.960
PF5	1.025	0.735	0.697	1.058	0.700	0.731	1.053	0.848	0.873	1.024	0.925	0.958	1.009	0.969	0.998
PF6	0.970	0.684	0.668	1.053	0.668	0.723	1.062	0.842	0.883	1.037	0.929	0.974	1.017	0.969	1.004
PF7	1.091	0.822	0.798	1.024	0.674	0.729	0.990	0.793	0.835	1.053	0.963	0.999	0.994	0.958	0.985
PF8	1.106	0.847	0.854	1.143	0.778	0.861	1.068	0.850	0.904	1.030	0.934	0.986	0.957	0.911	0.951
PF9	1.125	0.841	0.860	1.090	0.721	0.832	1.096	0.886	0.966	1.058	0.962	1.033	0.973	0.931	0.982
PF10	1.157	0.824	0.889	1.174	0.735	0.935	1.118	0.896	1.028	1.101	1.014	1.130	1.067	1.040	1.114
10-1	0.894***	0.959***	1.057***	0.394*	0.524**	0.633**	0.273	0.382*	0.450*	0.258*	0.330**	0.387**	0.143	0.166	0.209*
t(10-1)	(3.200)	(3.413)	(3.748)	(1.291)	(1.648)	(1.900)	(1.011)	(1.347)	(1.546)	(1.452)	(1.818)	(2.084)	(1.082)	(1.176)	(1.466)

This table shows the $k-th$ month ahead performance of stock portfolios constructed on the basis of filtered expected risk premia (FERP). FERP is estimated based on the second and third-order risk-neutral cumulants with the procedures introduced in the main text. At the end of each month t, stocks are sorted into decile portfolios based on their FERP. Portfolio 1 contains the stocks with the lowest FERP while Portfolio 10 includes the highest ones. A high-minus-low spread portfolio is also formed. The data sample covers the period from January 1996 to December 2017. These portfolios are held over the $t+k$ months, where k equals to 1, 2, 3, 6, and 12, and their equal-weighted monthly excess returns as well as risk-adjusted alphas are reported. *Ret* stands for the average $t+k$ monthly portfolio's risk premium and $\alpha_{\cdot}$ stands for the $t+k$ monthly portfolio's alpha estimated from different models. α_{FF3} and α_{FFC} represent the risk-adjusted alpha from the Fama-French three-factor model and the Carhart four-factor model, respectively. The Newey-West t-statistics with four lags are provided in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 3.11: Risk-Adjusted Portfolio Returns of Subsamples

	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	10-1
Panel A: Subsample: 1996 - 2006											
Ret	0.384	0.817	0.978	1.052	1.245	1.050	1.156	1.217	1.228	1.012	0.629*
	(0.766)	(2.237)	(3.231)	(3.914)	(4.668)	(3.922)	(4.394)	(4.582)	(4.391)	(2.494)	(1.516)
FF3-Alpha	-0.194	0.352	0.530	0.596	0.799	0.610	0.734	0.819	0.857	0.599	0.793**
	(-0.450)	(1.110)	(2.350)	(3.505)	(4.802)	(3.575)	(4.203)	(4.799)	(4.461)	(2.456)	(1.808)
FF-Carhart-Alpha	-0.218	0.344	0.520	0.604	0.780	0.613	0.718	0.839	0.890	0.678	0.896**
	(-0.514)	(1.096)	(2.218)	(3.448)	(4.434)	(3.554)	(3.997)	(5.001)	(4.521)	(2.667)	(2.077)
Panel B: Subsample: 2007 - 2017											
	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	10-1
Ret	0.143	0.444	0.625	0.738	0.806	0.891	1.027	0.996	1.022	1.300	1.157***
	(0.262)	(0.916)	(1.387)	(1.796)	(2.106)	(2.275)	(2.855)	(2.826)	(2.737)	(2.469)	(3.152)
FF3-Alpha	-0.191	0.079	0.289	0.434	0.481	0.569	0.726	0.743	0.784	1.056	1.246***
	(-0.538)	(0.260)	(0.962)	(1.662)	(2.133)	(2.508)	(3.569)	(3.489)	(3.530)	(2.910)	(3.413)
FF-Carhart-Alpha	-0.201	0.064	0.273	0.417	0.471	0.564	0.721	0.746	0.788	1.071	1.272***
	(-0.565)	(0.210)	(0.922)	(1.638)	(2.124)	(2.481)	(3.529)	(3.441)	(3.467)	(2.987)	(3.622)

This table reports monthly realized risk premia and risk-adjusted alphas of the filtered expected risk premium-sorted decile portfolios for two subsamples: 1996-2006 and 2007-2017. At the end of each month, stocks are sorted into decile portfolios based on their filtered expected risk premia (FERP). Then these portfolios are held over the next month and their monthly equal-weighted risk premia and commonly used risk factors adjusted alphas are presented. The FERP-based high-minus-low spread portfolios' risk premia are also presented in the last column. The Newey-West t-statistics with four lags are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 3.12: Risk-Adjusted Portfolio Returns of Single-Factor Case

	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	10-1
Ret	0.224	0.542	0.661	0.784	0.793	0.785	0.906	0.894	0.955	0.997	0.772***
	(0.787)	(2.234)	(3.134)	(3.929)	(3.964)	(3.936)	(4.626)	(4.406)	(4.065)	(3.452)	(2.884)
FF3-Alpha	-0.070	0.260	0.419	0.538	0.549	0.538	0.676	0.662	0.705	0.732	0.802***
	(-0.324)	(1.475)	(2.853)	(4.151)	(4.258)	(4.169)	(5.369)	(4.899)	(4.329)	(3.406)	(2.987)
FF-Carhart-Alpha	-0.120	0.216	0.378	0.511	0.523	0.524	0.653	0.675	0.727	0.796	0.917***
	(-0.555)	(1.221)	(2.508)	(3.829)	(3.924)	(3.977)	(4.998)	(4.804)	(4.201)	(3.607)	(3.444)

This table reports monthly realized risk premia and risk-adjusted alphas of the filtered expected risk premium-sorted decile portfolios. Filtered expected risk premium (FERP) is estimated under the single-factor model setup. At the end of each month, stocks are sorted into decile portfolios based on their FERP. Then these portfolios are held over the next month and their average monthly equal-weighted risk premia and commonly used risk factors adjusted alphas are presented. The FERP-based high-minus-low spread portfolios' risk premia are also presented in the last column. The Newey-West t-statistics with four lags are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 3.13: Filtered Expected Risk Premium and Fama-MacBeth Regressions - Single-Factor Case

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13
Intercept	0.813	0.596	-0.047	0.518	0.874	0.427	-0.157	0.490	0.253	0.488	2.220	1.570	2.422
	(4.912)	(0.820)	(-0.055)	(0.691)	(0.919)	(0.597)	(-0.220)	(0.669)	(0.317)	(0.596)	(2.901)	(1.878)	(2.375)
FERP	0.763***	0.786***	0.709***	0.767***	0.732***	0.764***	0.718***	0.805***	0.728***	0.743***	0.737***	0.330***	0.328***
	(3.987)	(4.198)	(4.117)	(4.166)	(4.063)	(3.990)	(4.191)	(4.302)	(4.191)	(4.220)	(3.988)	(2.573)	(2.517)
$BETA^Q$	-	0.099	0.089	0.098	0.096	0.096	0.103	0.101	0.093	0.093	0.115	0.063	0.072
	-	(4.022)	(3.889)	(3.827)	(4.003)	(4.061)	(4.041)	(4.226)	(3.977)	(3.904)	(4.628)	(1.566)	(1.840)
MV	-	-0.012	0.023	-0.013	-0.026	-0.008	0.003	-0.012	0.004	-0.003	-0.056	-0.031	-0.065
	-	(-0.436)	(0.679)	(-0.442)	(-0.710)	(-0.284)	(0.117)	(-0.422)	(0.129)	(-0.093)	(-1.914)	(-1.088)	(-1.748)
MOM	-	0.032	0.032	0.036	0.032	0.032	0.033	0.032	0.032	0.032	0.032	0.031	0.035
	-	(18.886)	(18.610)	(20.974)	(18.845)	(19.324)	(20.317)	(19.504)	(18.850)	(18.752)	(19.089)	(19.047)	(22.735)
B2M	-	0.063	0.063	0.064	0.059	0.059	0.073	0.070	0.061	0.061	0.066	0.060	0.056
	-	(0.751)	(0.762)	(0.740)	(0.702)	(0.690)	(0.867)	(0.844)	(0.732)	(0.730)	(0.797)	(0.729)	(0.705)
SVOLU	-	-	-0.069	-	-	-	-	-	-	-	-	-	-0.223
	-	-	(-2.298)	-	-	-	-	-	-	-	-	-	(-3.474)
REV	-	-	-	-0.043	-	-	-	-	-	-	-	-	-0.050
	-	-	-	(-16.138)	-	-	-	-	-	-	-	-	(-13.482)
ILLIQ	-	-	-	-	-0.026	-	-	-	-	-	-	-	-0.010
	-	-	-	-	(-0.971)	-	-	-	-	-	-	-	(-0.413)
MAX	-	-	-	-	-	0.001	-	-	-	-	-	-	0.079
	-	-	-	-	-	(0.109)	-	-	-	-	-	-	(6.776)
MIN	-	-	-	-	-	-	-0.094	-	-	-	-	-	-0.024
	-	-	-	-	-	-	(-8.953)	-	-	-	-	-	(-2.463)
ZS	-	-	-	-	-	-	-	-0.055	-	-	-	-	-0.072
	-	-	-	-	-	-	-	(-2.502)	-	-	-	-	(-3.443)
OVOLU	-	-	-	-	-	-	-	-	-0.096	-	-	-	0.218
	-	-	-	-	-	-	-	-	(-0.741)	-	-	-	(0.906)
OI	-	-	-	-	-	-	-	-	-	-0.044	-	-	0.412
	-	-	-	-	-	-	-	-	-	(-0.374)	-	-	(1.808)
P2AR	-	-	-	-	-	-	-	-	-	-	-1.360	-	-1.365
	-	-	-	-	-	-	-	-	-	-	(-7.064)	-	(-8.456)
IVOL	-	-	-	-	-	-	-	-	-	-	-	-1.637	-3.102
	-	-	-	-	-	-	-	-	-	-	-	(-2.526)	(-5.113)
ISKEW	-	-	-	-	-	-	-	-	-	-	-	-0.149	-0.226
	-	-	-	-	-	-	-	-	-	-	-	(-1.881)	(-2.898)
IKURT	-	-	-	-	-	-	-	-	-	-	-	0.003	0.093
	-	-	-	-	-	-	-	-	-	-	-	(0.091)	(2.899)
$Adj-R^2$	0.063	0.163	0.170	0.179	0.168	0.171	0.173	0.172	0.169	0.169	0.170	0.184	0.243
	(11.488)	(21.420)	(22.100)	(24.211)	(22.327)	(22.086)	(22.955)	(22.307)	(22.056)	(21.989)	(22.347)	(24.214)	(30.702)

This table reports the Fama-MacBeth coefficients of cross-sectional regressions of monthly realized risk premia on lagged ex-ante filtered expected risk premia (FERP) and a set of frequently used firm characteristics in the literature. FERP is estimated from the second and third-order risk-neutral cumulants with the PLS-based procedures introduced in the main text under a single-factor model framework. Model 1 (M1) only consider the FERP. Firms' risk-neutral beta ($BETA^Q$), market value (MV), momentum (MOM), and book-to-market ratio ($B2M$) are controlled in Models 2-13 (M2-M13). Model 3 additionally controls for stock trading volume ($SVOLU$). Model 4 additionally controls for 1-month reversal (REV). Model 5 controls for stock illiquidity proxied by Amihud's (2002) price impact ratio ($ILLIQ$). Model 6 and 7 additionally control for the maximum (MAX) and minimum (MIN) daily returns over the previous month, respectively. Model 8 additionally controls for firms' default risk (ZS). Model 9 and 10 additionally control for the trading volume of options used to compute risk-neutral cumulants ($OVOLU$) and options open interest (OI), respectively. Model 11 additionally controls for put-to-all options volume ratio ($P2AR$). Model 12 additionally control for 30-day maturity risk-neutral volatility ($IVOL$), risk-neutral skewness ($ISKEW$), and risk-neutral kurtosis ($IKURT$). Finally, Model 13 considers all the above mentioned variables. The second last row presents adjusted R^2. Data sample covers the period from January 1996 to December 2017. The Newey-West t-statistics with four lags are provided in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 3.14: Short-Selling Constraints and Filtered Expected Risk Premium

	Panel A: Relative Short Interest (RSI)						Panel B: Estimated Shorting Fee (ESF)						Panel C: Idiosyncratic Volatility ($IdioV$)					
	FERP1	FERP2	FERP3	FERP4	FERP5	5-1	FERP1	FERP2	FERP3	FERP4	FERP5	5-1	FERP1	FERP2	FERP3	FERP4	FERP5	5-1
SS1	0.761	1.012	1.129	1.019	1.277	0.515	0.824	0.967	0.939	1.118	1.196	0.372	0.954	0.966	0.976	1.205	1.192	0.238
	(2.484)	(4.679)	(5.666)	(5.095)	(4.915)	(2.495)	(2.375)	(3.817)	(4.112)	(4.979)	(4.634)	(1.457)	(4.349)	(5.242)	(5.004)	(7.490)	(7.295)	(1.672)
SS2	0.619	0.984	1.024	1.114	1.239	0.620	0.602	0.974	0.901	1.073	1.194	0.593	0.913	0.897	1.069	1.171	1.223	0.310
	(2.062)	(4.284)	(4.505)	(5.332)	(5.231)	(2.727)	(1.963)	(4.166)	(3.832)	(5.179)	(5.000)	(2.652)	(3.925)	(4.007)	(5.331)	(5.950)	(5.983)	(2.320)
SS3	0.616	0.874	0.990	1.008	1.115	0.499	0.535	0.929	0.955	1.027	0.967	0.433	0.735	0.850	0.944	1.018	1.200	0.465
	(1.931)	(3.237)	(4.103)	(4.488)	(3.912)	(2.392)	(1.816)	(3.698)	(4.072)	(4.481)	(4.049)	(2.004)	(2.646)	(3.573)	(3.921)	(4.207)	(4.954)	(2.864)
SS4	0.468	0.858	0.867	1.003	0.930	0.462	0.487	0.657	0.874	0.964	1.100	0.613	0.540	0.720	0.895	1.008	1.207	0.667
	(1.439)	(3.234)	(3.190)	(3.908)	(3.620)	(2.159)	(1.465)	(2.406)	(4.068)	(4.288)	(3.801)	(2.530)	(1.698)	(2.576)	(3.188)	(3.761)	(3.696)	(3.588)
SS5	0.034	0.543	0.662	0.884	0.808	0.774	0.084	0.738	0.888	0.916	0.938	0.854	0.013	0.365	0.585	0.609	0.595	0.582
	(0.090)	(1.621)	(1.950)	(2.654)	(2.114)	(2.645)	(0.218)	(2.167)	(2.461)	(2.524)	(2.445)	(3.328)	(0.030)	(0.929)	(1.619)	(1.458)	(1.369)	(2.021)
5-1	-0.727	-0.469	-0.467	-0.135	-0.468	-	-0.740	-0.229	-0.051	-0.202	-0.258	-	-0.941	-0.601	-0.391	-0.596	-0.597	-
	(-2.936)	(-2.001)	(-1.958)	(-0.618)	(-2.009)	-	(-2.441)	(-1.169)	(-0.256)	(-0.912)	(-1.033)	-	(-2.777)	(-2.172)	(-1.477)	(-1.877)	(-1.852)	-

This table reports the performance (monthly risk premium in %) of conditional double-sort portfolios constructed on the basis of the filtered expected risk premium (FERP) and each of the short-selling (SS) constraints proxies, during the period January 1996 - December 2017. I use the following three proxies for short-selling constraints: Relative Short Interest (RSI) in Panel A, Estimated Shorting Fee (ESF) in Panel B and the Idiosyncratic Volatility under physical measure ($IdioV$) in Panel C. At the end of each month in my sample, I first sort all stocks into quintile portfolios based on each of the above proxies of short-selling constraints, and then I sort stocks in each of these quintile portfolios into quintile portfolios based on the FERP. High-minus-low spread portfolios are formed with respect to the FERP and the proxies of short selling constraints, respectively. I hold these portfolios over the next month and compute their equal-weighted risk premia. The Newey-West t-statistics with four lags are provided in parentheses.

Table 3.15: Short-Selling Constraints and Relative Trading Activity

	Panel A: RSI		Panel B: ESF		Panel C: $IdioV$	
	Model	Model2	Model3	Model4	Model5	Model6
Intercept	10.487	-195.041	10.268	-201.641	7.856	-168.665
	(19.454)	(-11.196)	(18.492)	(-11.491)	(17.062)	(-11.160)
RSI/ESF/IdioV	0.041***	0.146***	3.251***	14.629***	3.256***	6.035***
	(12.114)	(15.538)	(10.310)	(14.015)	(8.942)	(10.070)
$BETA^P$	-	1.916	-	1.936	-	1.443
	-	(8.156)	-	(8.364)	-	(6.895)
MV	-	8.505	-	8.701	-	7.301
	-	(11.701)	-	(11.988)	-	(11.662)
B2M	-	-1.118	-	-0.709	-	-0.956
	-	(-4.715)	-	(-3.239)	-	(-3.082)
ILLIQ	-	2.998	-	2.981	-	2.840
	-	(5.992)	-	(6.082)	-	(5.838)
$Adj - R^2$	0.011	0.255	0.010	0.258	0.025	0.236
	(8.528)	(45.907)	(8.224)	(45.017)	(10.396)	(36.306)

This table reports the Fama-MacBeth cross-sectional regressions of the proxy of relative trading activity on the proxy of short-selling constraint. To measure relative trading activity, I use the ratio of trading volume in options to the trading volume in stocks (see Johnson and So (2012)). For measuring short-selling constraint, I use three proxies: the relative short interest RSI (see Asquith, Pathak, and Ritter (2005)), the estimated shorting fee ESF (see Boehme, Danielsen, and Sorescu (2006)), and the idiosyncratic volatility under physical measure $IdioV$ (see Wurgler and Zhuravskaya (2002)). Panel A shows the results by using RSI as the proxy of short-selling constraint. Panel B use ESF as the proxy of short-selling constraint. Panel C presents the results with $IdioV$ as the proxy of short-selling constraint. For each Panel, I run a single-factor regression as well as a multi-factor regression. In the former regression, the only explanatory variable is the proxy of short-selling constraint, while in the latter regression, I additionally control for commonly used variables such as market beta ($BETA^P$) under physical measure, market value (MV), book-to-market ratio ($B2M$), and the illiquidity ($ILLIQ$) of Amihud (2002). Data sample covers the period from January 1996 to December 2017. The Newey-West t-statistics with four lags are provided in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 3.16: Predictability of Filtered Expected Risk Premium and Liquidity

	Option Volume		Open Interest	
	M1	M2	M3	M4
Intercept	0.914	-1.169	0.927	-0.999
	(4.026)	(-0.898)	(3.905)	(-0.742)
FERP	0.157***	0.086***	0.165***	0.080***
	(2.982)	(2.363)	(3.046)	(2.060)
$FERP \times HOLS$	0.346**	0.408**	0.324	0.291
	(1.723)	(2.003)	(1.072)	(1.045)
$FERP \times LOHS$	-0.056	-0.070	0.055	0.081
	(-0.411)	(-0.655)	(0.307)	(0.548)
$BETA^P$	-	0.058	-	0.038
	-	(0.449)	-	(0.273)
MV	-	0.126	-	0.123
	-	(2.422)	-	(2.294)
B2M	-	-0.227	-	-0.241
	-	(-1.848)	-	(-1.928)
SVOLU	-	-0.001	-	-0.001
	-	(-1.911)	-	(-2.293)
IVOL	-	-0.646	-	-0.984
	-	(-0.897)	-	(-1.341)
ISKEW	-	-0.538	-	-0.508
	-	(-5.920)	-	(-5.511)
IKURT	-	-0.072	-	-0.061
	-	(-1.693)	-	(-1.370)
$Adj-R^2$	0.063	0.161	0.063	0.161
	(11.119)	(17.386)	(11.010)	(17.177)
F-test	1.502	1.454	1.520	1.388
pval	[0.000]	[0.000]	[0.000]	[0.000]

This table reports the Fama-MacBeth cross-sectional regressions of stocks' risk premia on the lagged filtered expected risk premia (FERP) and the relative liquidity of stocks and options. To measure stock liquidity, I use Amihud (2002) illiquidity ratio, and to measure option liquidity, I use option volume and option open interest. Two dummy variables are constructed to measure the relative liquidity of stocks and options. The first one is high option liquidity and low stock liquidity dummy, denoted as $HOLS$, and the other is low option liquidity and high stock liquidity dummy, denoted as $LOHS$. $HOLS$ is equal to one for stocks that belong to top 33% of option liquidity and the bottom 33% of stock liquidity. $LOHS$ is equal to one for stocks that belong to the bottom 33% of option liquidity and the top 33% of stock liquidity. Several frequently used variables such as market beta ($BETA^P$) under physical measure, market value (MV), book-to-market ratio ($B2M$), stock trading volume ($SVOLU$), option implied short-term volatility ($IVOL$), skewness ($ISKEW$), and kurtosis ($IKURT$) are also added into regression as additional control variables. F-test is for testing equal coefficients on two dummy-related variables and their related p-values are reported in square brackets. The Newey-West t-statistics with four lags are presented in parentheses. Data sample covers the period from January 1996 to December 2017. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

3.9 Appendix: Definitions of Control Variables

This Appendix presents detailed definitions of the control variables used in the empirical analysis.
Market beta under risk-neutral measure ($BETA^Q$)

- Risk-neutral market beta is calculated by using the method proposed by Chang et al. (2011), and it is given by

$$\beta^Q_{i,M} = (\frac{SKEW^Q_{i,t}}{SKEW^Q_{M,t}})^{1/3}\frac{VOL^Q_{i,t}}{VOL^Q_{M,t}}$$

  where $SKEW^Q_{i,t}$ and $SKEW^Q_{M,t}$ are option-implied skewness on stock i and the S&P 500 index, respectively, $VOL^Q_{i,t}$ and $VOL^Q_{M,t}$ are option-implied volatility for stock i and the S&P 500 index, respectively. The monthly beta is calculated by using option contracts with 30-day maturity.

Market beta under physical measure ($BETA^P$)

- Market beta under physical measure is the coefficient on market risk premium from the regression of excess daily stock returns on market risk premium within the month. I use the excess return on the S&P 500 index as a proxy of market risk premium.

Market value (MV)

- The market capitalization, which is defined as the closing share price times the number of shares outstanding.

Book-to-market ratio ($B2M$)

- The book to market ratio, which is computed as a logarithm of the ratio of Book Value over Market Value. The annual book value of the latest available is employed.

Momentum (MOM)

- Momentum for firm i in month t is defined as its cumulative stock return from the end of month $t-12$ to the end of month $t-1$.

Stock volume ($SVOLU$)

- The stock volume is the total volumes of traded stocks for the firm i during the whole month.

Reversal (REV)

- Reversal for firm i in month t is given by its monthly excess return in the previous month $t-1$.

Maximum daily return (MAX)

- The maximum of daily returns for firm i during the month t is defined as the highest daily stock return in the previous month $t-1$.

Minimum daily return (MIN)

- The minimum of daily returns for firm i during the month t is defined as the lowest daily stock return in the previous month $t-1$.

Stock illiquidity ($ILLIQ$)

- The stock illiquidity is computed with the method proposed by Amihud (2002). Specifically, we use Amihud (2002) price impact ratio to proxy for stock illiquidity. In particular, this price impact ratio for stock i over a month m is defined as

$$ILLIQ_{i,m} = \frac{\sum_{d=1}^{D_{i,m}} |R_{i,d}|}{VOLD_{i,d}} \times \frac{1}{D_{i,m}}$$

  where $|R_{i,d}|$ is the absolute daily stock return for firm i on day d, $VOLD_{i,d}$ is the dollar trading volume of stock i on day d, and $D_{i,m}$ is the number of trading days during month m. I compute $ILLIQ_{i,m}$ whenever there are at least 10 trading days for stock i within a month.

Default risk (ZS)

- I follow Acharya et al. (2013) and Stilger et al. (2016), and measure the default risk of firm i by using the Zmijewski (1984) Z-score, which is a weighted index of firm's ratios of net income (NI) to total assets (AT), total debt (LT) to total assets and current assets (ACT) to current liabilities (LCT). With the items in the Compustat, the Z-score is computed as:

$$ZS = -4.3 - 4.5\frac{NI}{AT} + 5.7\frac{LT}{AT} - 0.004\frac{ACT}{LCT}$$

Option volume ($OVOLU$)

- Option volume for firm i is computed as the sum of option volume across all put and call options for all maturities.

Option open interest (OI)

- Open interest for firm i is calculated as the sum of open interest across all put and call options for all maturities on a given trading day. The monthly open interest is the mean of the daily open interest within the month.

Put-to-all options volume ratio ($P2AR$)

- The put-to-all options volume ratio on a given trading day is the ratio of the total volume across all put options divided by the total volume across all put and call options. The options are the ones used for calculating risk-neutral cumulants.

Relative short interest (RSI)

- The relative short interest is calculated as the ratio of the number of short interest to the number of outstanding share. The short interest rate is obtained from the Compustat through the WRDS. The Compustat records the short interest at the middle of any given month until 2007, and then it starts to provide the short interest at the middle of months and the end of months. I use the end-of-month short interest data since 2007 because the extracted filter used in the paper based on the end-of-month risk-neutral cumulants.

Estimated shorting fee (ESF)

- To calculate the estimated shorting fee, I follow Boehme et al. (2006) and the ESF is given by

$$
\begin{aligned}
ESF = 0.07834 + 0.05438VRSI - 0.00664VRSI^2 + 0.000382VRSI^3 \\
-0.5908Option + 0.2587Option \cdot VRSI - 0.02713Option \cdot VRSI^2 \\
+0.0007583Option \cdot VRSI^3
\end{aligned}
$$

  where RSI is the relative short interest and $VRSI$ is the vicile rank of RSI, that is, $VRSI$ takes value 1 if the firm's RSI is below 5th percentile, 2 if the firm's RSI is between 5th and 10th percentile and so on. *Option* is a dummy variable that takes the value 1 if there is non-zero trading volume for the firm's options in the month and 0 otherwise. Option trading volume data is obtained from the OptionMetrics database via WRDS.

Idiosyncratic volatility under physical measure ($IdioV$)

- $IdioV$ for firm i in month t is computed as

$$IdioV = (\frac{1}{N(d)-1}\sum_{d\in D}\epsilon_{i,d}^2)^{1/2}$$

where $\epsilon_{i,d}$ is the daily firm-level residul of the Fama and French (1993) three-factor model regression within the month t, D is the set of non-missing daily returns in the month and $N(d)$ denotes the number of samples in the same month. I require at least 10 observations in each month to calculate $IdioV$.

3.10 Appendix: Risk-Neutral Cumulants Computation

This Appendix shows the formulae for computing risk-neutral cumulants following Bakshi and Madan (2000) and Bakshi et al. (2003). Let the $\tau-$period return be given by the log price relative:

$$R(t,\tau) \equiv log(S(t+\tau)) - log(S(t)) \tag{3.10.1}$$

Define the payoff of the $\tau-$period quadratic, cubic and quartic contract, respectively, as:

$$H(S) = \begin{cases} R(t,\tau)^2 & \text{quadratic contract} \\ R(t,\tau)^3 & \text{cubic contract} \\ R(t,\tau)^4 & \text{quartic contract} \end{cases}$$

Building on Breeden and Litzenberger (1978), Carr and Madan (2001) and Bakshi and Madan (2000) show that any payoff function $H(S)$ that is twice continuously differentiable with respect to stock price S can be spanned by a portfolio of zero-coupon bond, stock, and a continuum of out-of-money options. In particular, we have

$$E^Q[e^{-r_f\tau}H(S)] = e^{-r_f\tau}(H(S_0) - S_0H^{'}(S_0)) + S_0H^{'}(S_0)$$
$$+ \int_{S_0}^{\infty} H^{''}(K)C(t,\tau,K)dK + \int_0^{S_0} H^{''}(K)P(t,\tau,K)dK$$

where $H^{'}(S_0)$ is the first-order derivative of the payoff function evaluated at a given point S_0, and $H^{''}(K)$ denotes the second-order derivative of the payoff function evaluated at K. Then, let $V_{t,\tau} \equiv E_t^Q[e^{-r_f\tau}R(t,\tau)^2]$, $W_{t,\tau} \equiv E_t^Q[e^{-r_f\tau}R(t,\tau)^3]$, and $X_{t,\tau} \equiv E_t^Q[e^{-r_f\tau}R(t,\tau)^4]$ represent the fair value of the respective payoff. These contracts are essentially contingent claims with payoffs equal to the second, third and fourth power of the log stock return, respectively. Based on the spanning results in equations (7)-(9) in Bakshi et al. (2003), $V_{t,\tau}$, $W_{t,\tau}$ and $X_{t,\tau}$

are given by:

$$V_{t,T} = 2\int_0^{S_{t,T}} (\frac{1+log(\frac{S_{t,T}}{K})}{K^2})P_{t,T}(K)dK + 2\int_{S_{t,T}}^{\infty} (\frac{1-log(\frac{K}{S_{t,T}})}{K^2})C_{t,T}(K)dK$$
$$W_{t,T} = -3\int_0^{S_{t,T}} \frac{log(\frac{S_{t,T}}{K})(2+log(\frac{S_{t,T}}{K}))}{K^2}P_{t,T}(K)dK+$$
$$3\int_{S_{t,T}}^{\infty} \frac{log(\frac{K}{S_{t,T}})(2-log(\frac{K}{S_{t,T}}))}{K^2}C_{t,T}(K)dK$$
$$X_{t,T} = 4\int_0^{S_{t,T}} \frac{(log(\frac{S_{t,T}}{K}))^2(3+log(\frac{S_{t,T}}{K}))}{K^2}P_{t,T}(K)dK+$$
$$4\int_{S_{t,T}}^{\infty} \frac{(log(\frac{K}{S_{t,T}}))^2(3-log(\frac{K}{S_{t,T}}))}{K^2}C_{t,T}(K)dK \quad (3.10.2)$$

With the above equations (3.10.2), I follow Bakshi et al. (2003) and compute the second, third, and fourth-order risk neutral cumulants at time t for each stock i with the following formulae:

$$CUM^{\tau}_{i,t}(2) = e^{r_f\tau}V_{t,\tau} - (\mu^Q_{t,\tau})^2 \quad (3.10.3)$$
$$CUM^{\tau}_{i,t}(3) = e^{r_f\tau}W_{t,\tau} - 3\mu^Q_{t,\tau}e^{r_f\tau}V_{t,\tau} + 2(\mu^Q_{t,\tau})^3 \quad (3.10.4)$$
$$CUM^{\tau}_{i,t}(4) = e^{r_f\tau}X_{t,\tau} - 4\mu^Q_{t,\tau}e^{r_f\tau}W_{t,\tau} + 6e^{r_f\tau}(\mu^Q_{t,\tau})^2V_{t,\tau} - 3(\mu^Q_{t,\tau})^4 \quad (3.10.5)$$

where r is the risk-free rate, and $\mu^Q_{t,\tau}$ is given by:

$$\mu^Q_{t,\tau} = exp(r_f\tau) - 1 - \frac{exp(r_f\tau)}{2}V_{t,\tau} - \frac{exp(r_f\tau)}{6}W_{t,\tau} - \frac{exp(r_f\tau)}{24}X_{t,\tau} \quad (3.10.6)$$

I used the data on individual equity options from 1996 through 2017 available through OptionMetrics. In particular, I download the volatility surface file, which contains the interpolated implied volatility on standardized options with respect to deltas and maturities for each security on each day. I employ out-of-money call options ($0 < \Delta < 0.50$) and out-of-money put options ($-0.50 < \Delta < 0$) to compute risk-neutral cumulants. To calculate the integrals in (3.10.2) in principle, we need a continuum of option prices. However, we do not have a continuum of option prices in a real world. To deal with this issue, I discretize the respected integrals and approximate them from the available options. In particular, I follow literature (see, for example, Chang et al. (2013) and Rehman and Vilkov (2012)) and interpolate implied volatilities for each maturity using a cubic spline across moneyness levels to obtain a continuum of implied volatilities. For moneyness levels below or above the available moneyness level in the market, I use the implied volatility of the lowest or highest available strike price. In terms of interpolation-extrapolation, I obtain a fine grid of 1001 implied volatilities for moneyness levels between 1/3 and 3. I then convert these implied volatilities into call and put prices using the Black-Scholes model. In particular, moneyness levels smaller than 100% are used to generate put prices and moneyness levels larger than 100% are used to generate call prices. After implementing above interpolation-extrapolation technique, I compute risk-neutral cumulants with the aforementioned formulae (3.10.3), (3.10.4), (3.10.5), and (3.10.6).

3.11 Appendix: Consistency of Filtered Expected Risk Premium

This Appendix provides details about consistency of the estimate obtained with the procedures proposed in Section 3.3. Follow Kelly and Pruitt (2015) and Light et al. (2017), I make the following assumptions to guarantee the estimation procedures in Section 3.3 yield a consistent estimate of the infeasible best forecast for multiple future risk premia using all available information.

Assumption 1. The sample cross-sectional variance matrix of latent factors is positive definite. In particular, for each period t, $Var(F_{i,t}) \xrightarrow{p} \Omega_t$ as $N \to \infty$, and Ω_t is positive definite.

Assumption 2. The sample cross-sectional variance matrix of factor loadings is positive definite. In particular, for all observed variables $\tau = 1, 2, ..., S$, $Var(\Gamma_{l,\tau}) \xrightarrow{p} \Delta$ as $S \to \infty$ and Δ is positive definite.

Assumption 3. Error terms and factor loadings are orthogonal to each other. In particular, for each period t and for each stock $i, i = 1, 2, ..., N$, $Cov(\Gamma_{l,\tau}, \varepsilon^{\tau}_{i,t}) \xrightarrow{p} 0$ as $S \to \infty$.

Assumption 4. Error terms and latent factors are orthogonal to each other. In particular, for each period t and for each observed characteristic $\tau, \tau = 1, 2, ..., S$, $Cov(F_{i,t}, \varepsilon^{\tau}_{i,t}) \xrightarrow{p} 0$ as $N \to \infty$.

Under the above assumptions, the expected risk premium, $\mu_{i,t}$, obtained by implementing the steps 1-3 in the main text is a consistent estimate of the unobservable best forecast of the future stock's risk premium. To make this argument clear, I first re-state the estimation procedures below and then re-write the regression slopes in Section 3.3 in a relatively formal matrix form. Consistent with Kelly and Pruitt (2015), I construct L factors $Z^l_t, l \in \{1, 2, ..., L\}$ as follows: I start from $Z^1_{i,t} = r_{i,t}$, that is, run cross-sectional regressions of standardized risk-neutral cumulant $CUM^{\tau}_{i,t-1}$ on $r_{i,t}$ for each τ, denote slopes as $\hat{\Gamma}^{\tau}_t$, and then regress $CUM^{\tau}_{i,t-1}$ on the obtained slopes $\hat{\Gamma}^{\tau}_t$ in the risk-neutral cumulant space for each individual stock i, denote slopes $\hat{F}_{i,t-1}$, and again, I run the cross-sectional regression of $r_{i,t}$ on the obtained slopes $\hat{F}_{i,t-1}$ and denote the residuals as the new factor $Z^2_{i,t}$. Then, I repeat these steps to construct all L factors. As opposed to the regression procedures, I express the above estimated slopes in a concise matrix form in order to postulate easily for the following proof.

Let $Z_t = [Z^1_t, Z^2_t, ..., Z^L_t]$ denotes the matrix of proxies constructed according to the above mentioned steps. Z_t is a $N \times L$ matrix. Denote $CUM_{t-1} = [CUM^1_{t-1}, ..., CUM^S_{t-1}]$ as the matrix of risk-neutral cumulants, which is $N \times S$ matrix. $r_t = [r_{1,t}, ..., r_{N,t}]'$ is the vector of stocks' risk premia. Then, the estimated $\hat{\Gamma}_t$ (in matrix form, $S \times L$ matrix) - run the cross-sectional regression of observed standardized risk-neutral cumulants on proxies - is given by

$$\hat{\Gamma}_t = CUM'_{t-1} D_N Z_t (Z'_t D_N Z_t)^{-1} \tag{3.11.1}$$
$$D_N = I_N - N^{-1} 1_N 1'_N$$

Similarly, the estimated $\hat{F}_{t-1}$ and $\hat{F}_t$ ($N \times L$ matrix) - run the cross-sectional regressions of CUM_{t-1} and CUM_t on $\hat{\Gamma}_t$ in the risk-neutral cumulants space - are given by

$$\hat{F}_{t-1} = CUM_{t-1} D_S \hat{\Gamma}_t (\hat{\Gamma}'_t D_S \hat{\Gamma}_t)^{-1} \tag{3.11.2}$$
$$\hat{F}_t = CUM_t D_S \hat{\Gamma}_t (\hat{\Gamma}'_t D_S \hat{\Gamma}_t)^{-1} \tag{3.11.3}$$
$$D_S = I_S - S^{-1} 1_S 1'_S$$

Then, the estimated coefficients $\hat{B}$ ($L \times 1$ matrix) and computed expected returns $\hat{\mu}_t$ ($N \times 1$ matrix) of the Step 3 in the main text - run cross-sectional regression of r_t on $\hat{F}_{t-1}$ - can be written as

$$\hat{B} = (\hat{F}'_{t-1} D_N \hat{F}_{t-1})^{-1} \hat{F}'_{t-1} D_N r_t \tag{3.11.4}$$
$$\hat{\mu}_t = \hat{F}_t (\hat{F}'_{t-1} D_N \hat{F}_{t-1})^{-1} \hat{F}'_{t-1} D_N r_t \tag{3.11.5}$$

Under the above matrix expression, I next show that $\hat{\mu}_t$ is a consistent estimate of the unobservable best forecast for future stocks' demeaned risk premia. In other words, I want to show

$$\hat{\mu}_t \xrightarrow[S \to \infty]{N \to \infty} D_N F_t B \tag{3.11.6}$$

Proof: To prove (3.11.6), I start from (3.11.5) and substitute equations (3.11.1)-(3.11.3) into equation (3.11.5), then $\hat{\mu}_t$ is given by

$$
\begin{aligned}
\hat{\mu}_t &= \hat{F}_t(\hat{F}_{t-1}^{'} D_N \hat{F}_{t-1})^{-1} \hat{F}_{t-1}^{'} D_N r_t \\
&\xlongequal[plug\ \hat{F}_{t-1}\ (3.11.2)]{plug\ \hat{F}_t\ (3.11.3)} \\
& CUM_t D_S \hat{\Gamma}_t (\hat{\Gamma}_t^{'} D_S \hat{\Gamma}_t)^{-1} \\
& \times [(CUM_{t-1} D_S \hat{\Gamma}_t (\hat{\Gamma}_t^{'} D_S \hat{\Gamma}_t)^{-1})^{'} D_N (CUM_{t-1} D_S \hat{\Gamma}_t (\hat{\Gamma}_t^{'} D_S \hat{\Gamma}_t)^{-1})]^{-1} \\
& \times (CUM_{t-1} D_S \hat{\Gamma}_t (\hat{\Gamma}_t^{'} D_S \hat{\Gamma}_t)^{-1})^{'} D_N r_t \\
&= \\
& CUM_t D_S \hat{\Gamma}_t (\hat{\Gamma}_t^{'} D_S \hat{\Gamma}_t)^{-1} \\
& \times [(\hat{\Gamma}_t^{'} D_S \hat{\Gamma}_t)^{-1} \hat{\Gamma}_t^{'} D_S CUM_{t-1}^{'} D_N CUM_{t-1} D_S \hat{\Gamma}_t (\hat{\Gamma}_t^{'} D_S \hat{\Gamma}_t)^{-1}]^{-1} \\
& \times (\hat{\Gamma}_t^{'} D_S \hat{\Gamma}_t)^{-1} \hat{\Gamma}_t^{'} D_S CUM_{t-1}^{'} D_N r_t \\
&= CUM_t D_S \hat{\Gamma}_t \times [\hat{\Gamma}_t^{'} D_S CUM_{t-1}^{'} D_N CUM_{t-1} D_S \hat{\Gamma}_t]^{-1} \times \hat{\Gamma}_t^{'} D_S CUM_{t-1}^{'} D_N r_t
\end{aligned} \tag{3.11.7}
$$

$$
\begin{aligned}
&\xlongequal[into\ (3.11.7)]{plug\ \hat{\Gamma}_t\ (3.11.1)} \\
& CUM_t D_S CUM_{t-1}^{'} D_N Z_t (Z_t^{'} D_N Z_t)^{-1} \\
& \times [(CUM_{t-1}^{'} D_N Z_t (Z_t^{'} D_N Z_t)^{-1})^{'} D_S CUM_{t-1}^{'} D_N CUM_{t-1} D_S (CUM_{t-1}^{'} D_N Z_t (Z_t^{'} D_N Z_t)^{-1})]^{-1} \\
& \times (CUM_{t-1}^{'} D_N Z_t (Z_t^{'} D_N Z_t)^{-1})^{'} D_S CUM_{t-1}^{'} D_N r_t \\
&= \\
& CUM_t D_S CUM_{t-1}^{'} D_N Z_t \\
& \times [Z_t^{'} D_N CUM_{t-1} D_S CUM_{t-1}^{'} D_N CUM_{t-1} D_S CUM_{t-1}^{'} D_N Z_t]^{-1} \\
& \times Z_t^{'} D_N CUM_{t-1} D_S CUM_{t-1}^{'} D_N r_t \\
&= \\
& CUM_t [CUM_{t-1}^{'} D_N CUM_{t-1}]^{-1} CUM_{t-1}^{'} D_N r_t
\end{aligned} \tag{3.11.8}
$$

Then, when $N, S \to \infty$, the (3.11.8) becomes

$$
plim_{N,S\to\infty} CUM_t [\frac{CUM_{t-1}^{'} D_N CUM_{t-1}}{N}]^{-1} \frac{CUM_{t-1}^{'} D_N r_t}{N} \tag{3.11.9}
$$

In the equation (3.11.9), the following parts can be computed

$$plim_{N\to\infty}\frac{CUM'_{t-1}D_N r_t}{N} \xlongequal[plug\ CUM_{t-1}]{plug\ r_t} plim_{N\to\infty}\frac{(F'_{t-1}\Gamma' D_N + \varepsilon'_{t-1})(D_N F_{t-1}B + D_N\epsilon_t)}{N} \xlongequal{Assumptions\ 1,3,4} \Gamma'\Omega_{t-1}B \quad (3.11.10)$$

$$plim_{N\to\infty}\frac{CUM'_{t-1}D_N CUM_{t-1}}{N} \xlongequal{plug\ CUM_{t-1}} plim_{N\to\infty}\frac{(F'_{t-1}\Gamma' D_N + \varepsilon'_{t-1})D_N(D_N\Gamma F_{t-1} + \varepsilon_{t-1})}{N} \xlongequal{Assumptions\ 1,3,4} \Gamma'\Omega_{t-1}\Gamma \quad (3.11.11)$$

Then equation (3.11.9) has the limit

$$plim_{N,S\to\infty}CUM_t[\frac{CUM'_{t-1}D_N CUM_{t-1}}{N}]^{-1}\frac{CUM'_{t-1}D_N r_t}{N} \xlongequal[CUM_t]{plug\ (3.11.10),(3.11.11)} plim_{S\to\infty}D_N F_t\Gamma(\Gamma'\Omega_{t-1}\Gamma)^{-1}\Gamma'\Omega_{t-1}B \xlongequal{Assumption2} D_N F_t B \quad (3.11.12)$$

This completes the proof. Q.E.D.

3.12 Appendix: Additional Results

3.12.1 Pair-Wise Correlations

For the control variables described in Table 3.3, the following Table A1 reports the time-series average of the cross-sectional pair-wise correlations during the period from 1996 to 2017.

Table A1: Correlations

	FERP	EWRet	MV	B2M	MOM	$BETA^P$	$BETA^Q$	ILLIQ	SVOLU	REV	MAX	MIN	ZS	OVOLU	OI	P2AR
FERP	1.00	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
EWRet	0.05	1.00	-	-	-	-	-	-	-	-	-	-	-	-	-	-
MV	0.02	0.04	1.00	-	-	-	-	-	-	-	-	-	-	-	-	-
B2M	-0.01	-0.02	-0.18	1.00	-	-	-	-	-	-	-	-	-	-	-	-
MOM	0.02	0.22	0.17	-0.16	1.00	-	-	-	-	-	-	-	-	-	-	-
$BETA^P$	-0.02	0.00	-0.05	0.04	0.03	1.00	-	-	-	-	-	-	-	-	-	-
$BETA^Q$	-0.03	0.02	0.01	-0.03	0.03	0.23	1.00	-	-	-	-	-	-	-	-	-
ILLIQ	0.00	0.00	-0.54	0.02	0.01	-0.02	-0.02	1.00	-	-	-	-	-	-	-	-
SVOLU	-0.01	-0.01	0.41	0.01	-0.01	0.16	0.05	-0.35	1.00	-	-	-	-	-	-	-
REV	-0.00	-0.01	0.06	-0.06	0.30	-0.03	0.00	0.01	-0.02	1.00	-	-	-	-	-	-
MAX	-0.02	0.00	-0.16	0.02	0.03	0.28	0.19	-0.02	0.13	0.31	1.00	-	-	-	-	-
MIN	0.02	-0.01	0.18	-0.05	0.14	-0.26	-0.17	0.03	-0.12	0.39	-0.34	1.00	-	-	-	-
ZS	-0.00	-0.03	-0.05	0.05	-0.08	-0.02	-0.02	-0.03	-0.05	-0.02	-0.05	0.03	1.00	-	-	-
OVOLU	-0.01	0.00	0.44	-0.03	0.04	0.12	0.07	-0.27	0.78	0.00	0.09	-0.08	-0.09	1.00	-	-
OI	-0.01	-0.00	0.47	0.00	-0.01	0.11	0.05	-0.31	0.87	-0.01	0.09	-0.08	-0.04	0.87	1.00	-
P2AR	-0.03	-0.06	-0.17	0.04	-0.05	-0.05	0.03	0.32	-0.17	-0.02	-0.09	0.06	0.02	-0.09	-0.12	1.00

3.12.2 Extra Robustness Check

In the main text, Table 3.9 and 3.13 report the average coefficients of Fama-MacBeth cross-sectional regressions with the risk-neutral market beta ($BETA^Q$) as a control variable, indicating that the $BETA^Q$ is significantly positively related to the future stock's risk premium although it does not affect the significant positive relationship between the ex-ante filtered expected risk premia and future stocks' risk premia. In this part, I repeat the above Fama-MacBeth regressions by replacing risk neutral market beta ($BETA^Q$) with physical measure market beta ($BETA^P$).

The above Table A2 reports the results from a two-factor setup (similar to Table 3.9) and the following Table A3 shows the average coefficients of Fama-MacBeth cross-sectional regressions with the FERP extracted from the second and third-order risk-neutral cumulants under a one-factor setup (similar to Table 3.13).

3.12.3 Option Pricing Implication of Filtered Latent Risk Factors for Individual Stocks

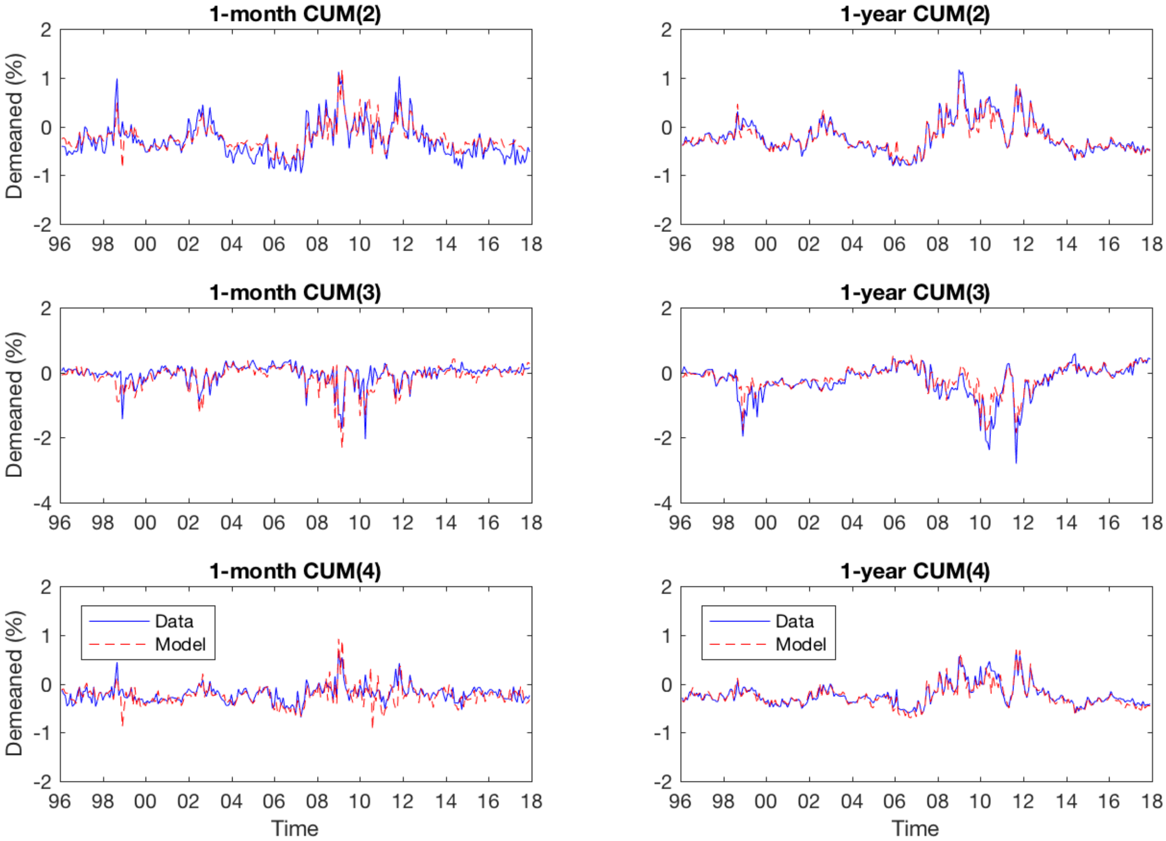


Figure 3.7: Model-implied and Data-implied risk-neutral cumulants at different orders with maturities at 1 month and 1 year for JP Morgan Chase & Co.: January 1996 - December 2017. CUM(n) stands for risk-neutral cumulant at the n-th order. Data-implied risk-neutral cumulant is calculated by the model-free method of Bakshi et al. (2003) and Model-implied risk-neutral cumulant is calculated as the product of filtered returns-related latent factors and factor loadings.

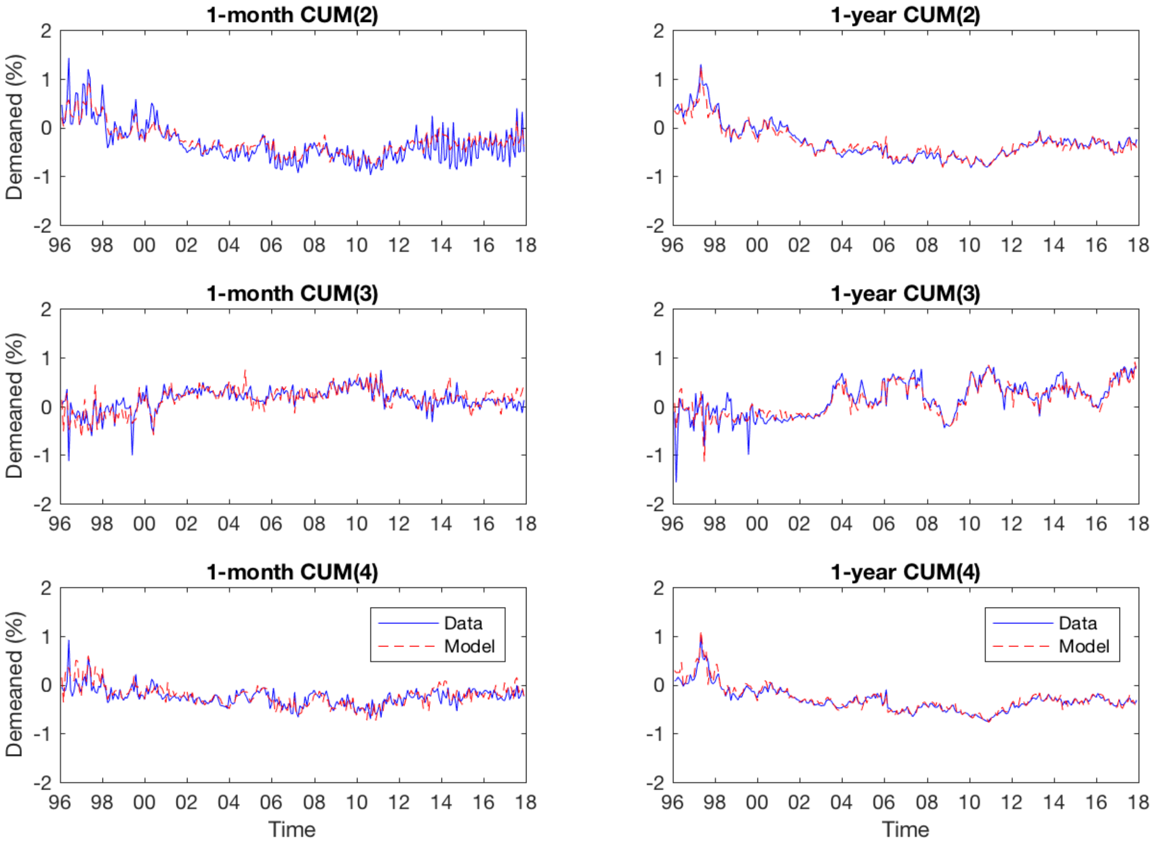


Figure 3.8: Model-implied and Data-implied risk-neutral cumulants at different orders with maturities at 1 month and 1 year for NIKE Inc.: January 1996 - December 2017. CUM(n) stands for risk-neutral cumulant at the n-th order. Data-implied risk-neutral cumulant is calculated by the model-free method of Bakshi et al. (2003) and Model-implied risk-neutral cumulant is calculated as the product of filtered returns-related latent factors and factor loadings.

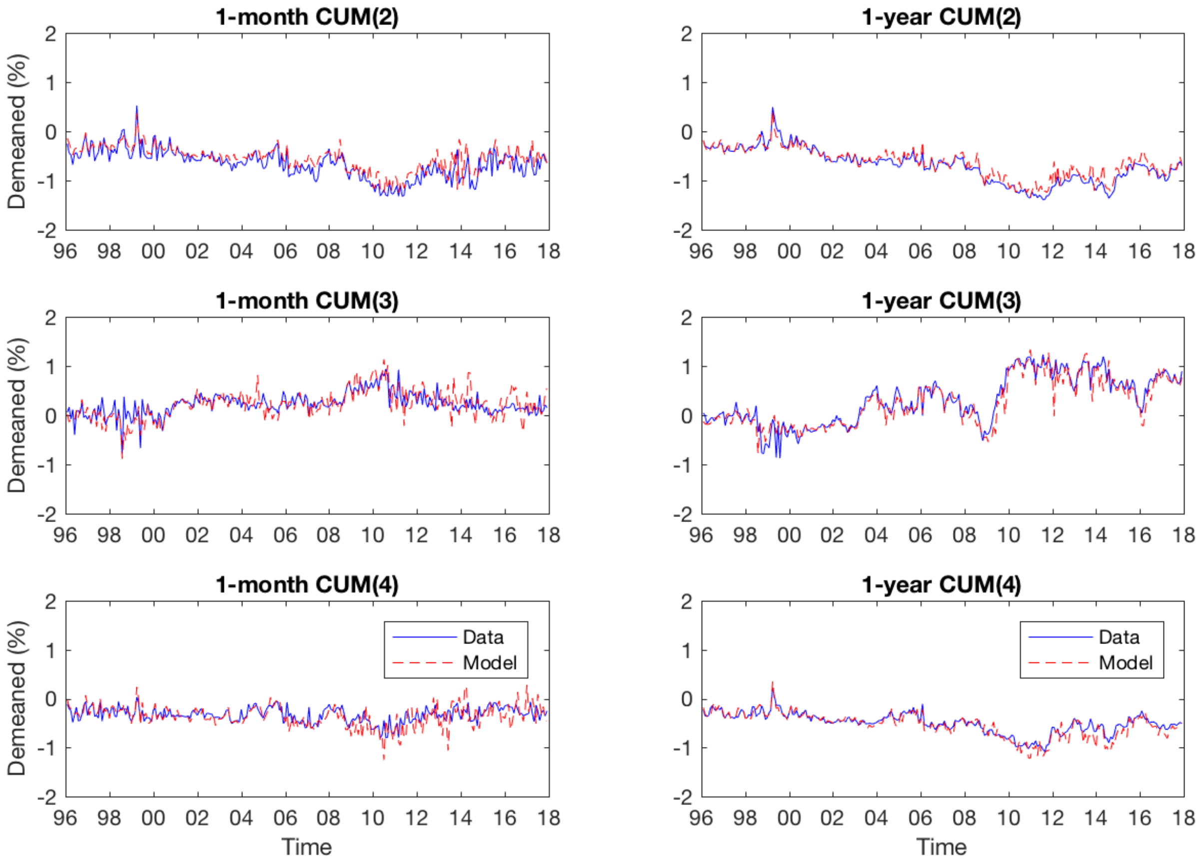


Figure 3.9: Model-implied and Data-implied risk-neutral cumulants at different orders with maturities at 1 month and 1 year for Walmart Inc.: January 1996 - December 2017. CUM(n) stands for risk-neutral cumulant at the n-th order. Data-implied risk-neutral cumulant is calculated by the model-free method of Bakshi et al. (2003) and Model-implied risk-neutral cumulant is calculated as the product of filtered returns-related latent factors and factor loadings.

Table A2: Filtered Expected Risk Premium and Fama-MacBeth Regressions

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13
Intercept	0.979	0.359	-0.427	0.389	0.509	0.175	-0.530	0.355	-0.126	0.158	2.313	1.383	3.865
	(4.951)	(0.409)	(-0.402)	(0.427)	(0.469)	(0.210)	(-0.625)	(0.404)	(-0.124)	(0.152)	(2.489)	(1.617)	(3.400)
FERP	0.128***	0.081***	0.083***	0.074***	0.083***	0.080***	0.085***	0.075***	0.074***	0.076***	0.078***	0.054**	0.058**
	(3.168)	(2.548)	(2.791)	(2.392)	(2.640)	(2.741)	(2.794)	(2.474)	(2.437)	(2.480)	(2.451)	(1.859)	(2.205)
$BETA^P$	-	-0.075	-0.051	-0.127	-0.067	-0.091	-0.144	-0.065	-0.078	-0.083	-0.075	0.053	-0.013
	-	(-0.777)	(-0.546)	(-1.294)	(-0.694)	(-0.995)	(-1.573)	(-0.662)	(-0.844)	(-0.885)	(-0.766)	(0.664)	(-0.164)
MV	-	0.001	0.039	-0.001	-0.006	0.006	0.027	-0.000	0.025	0.009	-0.050	-0.037	-0.093
	-	(0.035)	(0.901)	(-0.034)	(-0.141)	(0.189)	(0.785)	(-0.001)	(0.615)	(0.219)	(-1.400)	(-1.104)	(-2.120)
MOM	-	0.040	0.040	0.045	0.040	0.041	0.042	0.040	0.040	0.040	0.040	0.039	0.044
	-	(20.798)	(20.723)	(22.928)	(20.795)	(21.218)	(22.023)	(21.478)	(20.769)	(20.559)	(21.079)	(20.859)	(24.674)
B2M	-	0.084	0.076	0.102	0.087	0.084	0.112	0.090	0.075	0.066	0.088	0.045	0.063
	-	(0.842)	(0.789)	(1.034)	(0.886)	(0.855)	(1.133)	(0.930)	(0.760)	(0.677)	(0.891)	(0.479)	(0.719)
SVOLU	-	-	-0.089	-	-	-	-	-	-	-	-	-	-0.272
	-	-	(-2.241)	-	-	-	-	-	-	-	-	-	(-3.602)
REV	-	-	-	-0.051	-	-	-	-	-	-	-	-	-0.060
	-	-	-	(-16.456)	-	-	-	-	-	-	-	-	(-13.904)
ILLIQ	-	-	-	-	-0.023	-	-	-	-	-	-	-	-0.021
	-	-	-	-	(-0.652)	-	-	-	-	-	-	-	(-0.717)
MAX	-	-	-	-	-	-0.002	-	-	-	-	-	-	0.094
	-	-	-	-	-	(-0.124)	-	-	-	-	-	-	(6.958)
MIN	-	-	-	-	-	-	-0.106	-	-	-	-	-	-0.034
	-	-	-	-	-	-	(-7.679)	-	-	-	-	-	(-2.749)
ZS	-	-	-	-	-	-	-	-0.081	-	-	-	-	-0.090
	-	-	-	-	-	-	-	(-3.021)	-	-	-	-	(-3.641)
OVOLU	-	-	-	-	-	-	-	-	-0.161	-	-	-	0.297
	-	-	-	-	-	-	-	-	(-0.953)	-	-	-	(1.111)
OI	-	-	-	-	-	-	-	-	-	-0.038	-	-	0.488
	-	-	-	-	-	-	-	-	-	(-0.289)	-	-	(1.910)
P2AR	-	-	-	-	-	-	-	-	-	-	-1.681	-	-1.735
	-	-	-	-	-	-	-	-	-	-	(-7.522)	-	(-9.412)
IVOL	-	-	-	-	-	-	-	-	-	-	-	-0.579	-3.903
	-	-	-	-	-	-	-	-	-	-	-	(-0.495)	(-3.307)
ISKEW	-	-	-	-	-	-	-	-	-	-	-	-1.447	-2.056
	-	-	-	-	-	-	-	-	-	-	-	(-3.924)	(-5.810)
IKURT	-	-	-	-	-	-	-	-	-	-	-	-0.402	0.100
	-	-	-	-	-	-	-	-	-	-	-	(-1.430)	(0.345)
$Adj-R^2$	0.048	0.172	0.180	0.187	0.177	0.180	0.183	0.181	0.178	0.178	0.179	0.202	0.259
	(10.776)	(22.578)	(23.821)	(25.077)	(23.531)	(23.485)	(24.432)	(23.159)	(23.513)	(23.556)	(23.334)	(25.559)	(31.487)

This table reports the Fama-MacBeth coefficients of cross-sectional regressions of monthly realized risk premia on lagged filtered expected risk premia (FERP) and a set of frequently used firm characteristics in the literature. The FERP is estimated from the second and third-order risk-neutral cumulants with the procedures introduced in the main text. Model 1 (M1) only consider FERP. Firms' physical measure market beta ($BETA^P$), market value (MV), momentum (MOM), and book-to-market ratio ($B2M$) are controlled in Models 2-13 (M2-M13). Model 3 additionally controls for the stock trading volume ($SVOLU$). Model 4 additionally controls for 1-month reversal (REV). Model 5 controls for stock illiquidity proxied by Amihud's (2002) price impact ratio ($ILLIQ$). Model 6 and 7 additionally control for the maximum (MAX) and minimum (MIN) daily returns over the previous month, respectively. Model 8 additionally controls for firms' default risk (ZS). Model 9 and 10 additionally control for the trading volume of options used to compute risk-neutral cumulants ($OVOLU$) and options open interest (OI), respectively. Model 11 additionally controls for put-to-all options volume ratio ($P2AR$). Model 12 additionally control for 30-day maturity risk-neutral volatility ($IVOL$), risk-neutral skewness ($ISKEW$), and risk-neutral kurtosis ($IKURT$). Finally, Model 13 considers all the above mentioned variables. The second last row presents adjusted R^2. Data sample covers the period from January 1996 to December 2017. The Newey-West t-statistics with four lags are provided in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A3: Filtered Expected Risk Premium and Fama-MacBeth Regressions - Single-Factor Case

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13
Intercept	0.813	0.359	-0.341	0.331	0.586	0.240	-0.358	0.311	0.018	0.166	1.985	1.541	2.370
	(4.912)	(0.512)	(-0.399)	(0.457)	(0.649)	(0.355)	(-0.517)	(0.444)	(0.023)	(0.206)	(2.652)	(1.889)	(2.316)
FERP	0.763***	0.550***	0.503***	0.592***	0.539***	0.537***	0.574***	0.557***	0.507***	0.520***	0.558***	0.305***	0.278**
	(3.987)	(4.069)	(3.899)	(4.345)	(4.083)	(3.879)	(4.357)	(4.155)	(4.005)	(4.097)	(4.020)	(2.542)	(2.303)
$BETA^P$	-	-0.057	-0.037	-0.095	-0.048	-0.072	-0.102	-0.054	-0.051	-0.055	-0.061	0.019	-0.018
	-	(-0.801)	(-0.526)	(-1.289)	(-0.678)	(-1.031)	(-1.446)	(-0.761)	(-0.739)	(-0.788)	(-0.862)	(0.286)	(-0.272)
MV	-	-0.001	0.034	-0.001	-0.010	0.002	0.016	0.000	0.015	0.005	-0.039	-0.030	-0.062
	-	(-0.031)	(0.988)	(-0.047)	(-0.291)	(0.067)	(0.605)	(0.007)	(0.474)	(0.149)	(-1.383)	(-1.041)	(-1.632)
MOM	-	0.034	0.033	0.038	0.033	0.034	0.035	0.033	0.033	0.033	0.033	0.032	0.036
	-	(20.434)	(20.055)	(23.109)	(20.463)	(20.867)	(21.523)	(21.090)	(20.191)	(20.055)	(20.716)	(20.094)	(23.770)
B2M	-	0.083	0.077	0.086	0.081	0.080	0.099	0.075	0.085	0.079	0.067	0.055	0.048
	-	(0.986)	(0.951)	(1.027)	(0.968)	(0.958)	(1.197)	(0.922)	(1.036)	(0.978)	(0.819)	(0.667)	(0.635)
SVOLU	-	-	-0.080	-	-	-	-	-	-	-	-	-	-0.230
	-	-	(-2.406)	-	-	-	-	-	-	-	-	-	(-3.601)
REV	-	-	-	-0.044	-	-	-	-	-	-	-	-	-0.050
	-	-	-	(-17.329)	-	-	-	-	-	-	-	-	(-13.802)
ILLIQ	-	-	-	-	-0.026	-	-	-	-	-	-	-	-0.015
	-	-	-	-	(-0.985)	-	-	-	-	-	-	-	(-0.619)
MAX	-	-	-	-	-	-0.001	-	-	-	-	-	-	0.075
	-	-	-	-	-	(-0.048)	-	-	-	-	-	-	(6.651)
MIN	-	-	-	-	-	-	-0.091	-	-	-	-	-	-0.024
	-	-	-	-	-	-	(-8.748)	-	-	-	-	-	(-2.409)
ZS	-	-	-	-	-	-	-	-0.064	-	-	-	-	-0.075
	-	-	-	-	-	-	-	(-2.857)	-	-	-	-	(-3.542)
OVOLU	-	-	-	-	-	-	-	-	-0.118	-	-	-	0.246
	-	-	-	-	-	-	-	-	(-0.940)	-	-	-	(1.074)
OI	-	-	-	-	-	-	-	-	-	-0.038	-	-	0.407
	-	-	-	-	-	-	-	-	-	(-0.337)	-	-	(1.872)
P2AR	-	-	-	-	-	-	-	-	-	-	-1.369	-	-1.435
	-	-	-	-	-	-	-	-	-	-	(-7.801)	-	(-9.207)
IVOL	-	-	-	-	-	-	-	-	-	-	-	-1.662	-2.856
	-	-	-	-	-	-	-	-	-	-	-	(-2.751)	(-5.000)
ISKEW	-	-	-	-	-	-	-	-	-	-	-	-0.303	-0.371
	-	-	-	-	-	-	-	-	-	-	-	(-5.929)	(-6.965)
IKURT	-	-	-	-	-	-	-	-	-	-	-	-0.018	0.078
	-	-	-	-	-	-	-	-	-	-	-	(-0.608)	(2.632)
$Adj-R^2$	0.063	0.177	0.184	0.192	0.182	0.184	0.187	0.186	0.182	0.182	0.184	0.196	0.253
	(11.488)	(23.414)	(24.305)	(26.024)	(24.149)	(24.003)	(25.006)	(24.161)	(24.127)	(24.061)	(24.254)	(26.011)	(32.447)

This table reports the Fama-MacBeth coefficients of cross-sectional regressions of monthly realized risk premia on lagged filtered expected risk premia (FERP) and a set of frequently used firm characteristics in the literature. The FERP is extracted from the second and third-order risk-neutral cumulants with the procedures introduced in the main text under a single-factor model framework. Model 1 (M1) only consider FERP. Firms' physical measure market beta ($BETA^P$), market value (MV), momentum (MOM), and book-to-market ratio ($B2M$) are controlled in Models 2-13 (M2-M13). Model 3 additionally controls for stock trading volume ($SVOLU$). Model 4 additionally controls for 1-month reversal (REV). Model 5 controls for stock illiquidity proxied by Amihud's (2002) price impact ratio ($ILLIQ$). Model 6 and 7 additionally control for the maximum (MAX) and minimum (MIN) daily returns over the previous month, respectively. Model 8 additionally controls for firms' default risk (ZS). Model 9 and 10 additionally control for the trading volume of options used to compute risk-neutral cumulants ($OVOLU$) and options open interest (OI), respectively. Model 11 additionally controls for put-to-all options volume ratio ($P2AR$). Model 12 additionally control for 30-day maturity risk-neutral volatility ($IVOL$), risk-neutral skewness ($ISKEW$), and risk-neutral kurtosis ($IKURT$). Finally, Model 13 considers all the above mentioned variables. The second last row presents adjusted R^2. Data sample covers the period from January 1996 to December 2017. The Newey-West t-statistics with four lags are provided in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Chapter 4

A Bayesian Regime Switching Model of Consumption Dynamics and the Role of Higher Moments

4.1 Introduction

The natural economic explanation for differences in expected returns across assets is differences in risk. The conventional Capital Asset Pricing Model (CAPM) measures the risk of an asset by its market beta. It is observed that the stock market indices can account for a large proportion of the intertemporal variability in other stock or stock portfolios in the time series regressions. However, this contrasts sharply with the inability of the stock market indices' beta to explain the cross-sectional variation of expected stock returns. An alternative to the CAPM is the consumption-based CAPM, which is ranked as one of the major advances in financial economics in the last several decades. Different from the standard CAPM, consumption-based CAPM enables us to prescribe an agent's behavior through utility by virtue of consuming goods rather than earning wealth pe se. Moreover, consumption captures the effect of all the state variables that makes it to be a much more tractable variable than the market portfolio in CAPM.

In the standard representative-agent consumption CAPM (Lucas Jr (1978)), it measures the asset's systematic risk by the covariance of its return with overall aggregate marginal utility of consumption. An attractive feature of the consumption-based CAPM is that it models consumption and savings choices of investors simultaneously in the intertemporal setting, whereas the classical CAPM ignores consumption decisions. Although - based on the consumption-based CAPM theory - the differences in the covariance of returns and contemporaneous consumption growth across portfolios should be able to explain the differences in expected returns observed in the U.S. stock market, the classical consumption-based asset pricing models prove disappointing empirically. For example, Mankiw and Shapiro (1986) regress the average returns of the 464 NYSE stocks that were continuously traded from 1959 to 1982 on their market betas, on consumption growth betas, and on both betas. They find that market betas are more strongly and robustly associated with the cross section of average returns, and they find that market betas drive out consumption betas in multiple regressions. Breeden et al. (1989) study industry and bond portfolios, finding roughly comparable performance of the CAPM and a model that uses a mimicking portfolio for consumption growth as the single factor, after adjusting the consumption-based model for measurement problems in consumption. Cochrane (1996) finds that the traditional CAPM substantially outperforms the canonical consumption-based model in pricing size portfolios. For example, he reports a root mean square pricing error of 0.094% per quarter for the CAPM and 0.54% per quarter for the consumption-based model. Campbell and Cochrane (2000) give a nice review and explanation of the poor performance of consumption-based asset pricing models.

The canonical consumption-based model has failed perhaps the most important test of all. This history is often interpreted as evidence against consumption-based models in general rather than against particular utility functions, particular specifications of temporal nonseparabilities such as habit persistence or durability, and particular choices of consumption data and data-handling processors. But this conclusion is internally inconsistent, because all current asset-pricing models are derived as specializations of the consumption-based model rather than as alternative to it. Recent theoretical advances in the field includes the habit formation model of Campbell and Cochrane (1999), the long-run risk model of Bansal and Yaron (2004), and the rare disaster model of Barro (2006), who have provided new mechanisms for connecting financial asset prices to real economic quantities such as consumption growth. Besides, empirical evidence regarding consumption-based models' ability to capture cross-sectional variation in average returns has resulted in a new interest in understanding the links between consumption growth and asset prices, recently. For example, Parker and Julliard (2005) find that covariance of asset returns with future consumption growth has explanatory power for the cross-section of firms. Yogo (2006) derives a model with non-separable consumption of nondurable goods and shows that growth in durable goods consumption explains cross-sectional variation in returns. Jagannathan and Wang (2007) find that measuring consumption growth as the growth in year-on-year quarter consumption explains a substantial portion of cross-sectional variation in returns.

Despite the empirical shortcomings of the consumption-based model, the reputation of the theoretical paradigm itself remains well preserved. As a measure of systematic risk, an asset's covariance with the marginal utility of consumption has a degree of theoretical purity that is unmatched by other asset pricing models. These other models, including the static CAPM, can almost always be expressed as either special cases of, or proxies for, the consumption-based model. Moreover, the consumption-based framework is a simple but powerful tool for addressing the criticisms of Merton (1973), that the static CAPM fails to account for the intertemporal hedging component of asset demand, and Roll (1977), that the market return cannot be adequately proxied by an index of common stocks. According to these rationales, the puzzle is not which model should replace the consumption-based paradigm, but rather why there has been no confirmation of it empirically.

On the other hand, most models in finance are based on mean-variance analysis. The risk premium is therefore derived from the second moment of a random variable. The basic assumption of this kind of modeling is that agents are not concerned about moments higher than the variance. However, the unknown form of the return distribution is unlikely to be described by the first two moments only. There is mounting evidence that investors not only care about variance, but also care about higher moments risk. Moreover, their preferences seem to follow some standard behavior, in which they like odd moments and dislike even ones. For example, Harvey and Siddique (2000) propose an asset pricing model to incorporate conditional skewness and show that conditional systematic skewness helps explain the cross-sectional variation of expected stock returns. Dittmar (2002) indicates that preferences restricted nonlinear pricing kernels are both admissible for the cross section of returns and are able to significantly improve upon linear single- and multifactor kernels. More recently, Constantinides and Ghosh (2015) show that the third central moment of the cross-sectional household consumption growth distribution explains the cross section of excess returns on the size-sorted, book-to-market-equity-sorted, and industry-sorted portfolios. Colacito et al. (2016) find that skewness of expected marco fundamentals can predict equity excess returns. In this paper, I highlight the importance of higher moments of consumption risk in pricing asset returns in the cross section.

In particular, I study the Fama and French size and book-to-market portfolios and reevaluate the central insight of the consumption-based asset pricing model that an asset's expected returns is determined by its equilibrium risk to consumption. Rather than measure the risk of a portfolio by only the contemporaneous covariance of its return and consumption growth – as done in the previous literature on the consumption-based CAPM – I measure the risk of a portfolio by also highlighting the importance of higher moments of consumption growth. I follow the canonical consumption-based asset pricing model and assume that there exists a representative agent, allowing the pricing kernel to be expressed as a function of aggregate consumption. This specification is appealing from the standpoint of economic theory. However, an issue in this analysis is the form of the representative agent's utility function. A large body of literature investigates standard choices for the utility function and finds that the data imply unrealistic assumptions about investors' risk aversion or the riskless rate (see Mehra and Prescott (1985), Weil (1989), among others), implying that a suitable representation for the representative agent's utility function is unknown. To deal with this issue in this paper, I express the pricing kernel generally as a nonlinear function of the consumption growth. Specifically, I approximate the pricing kernel using a Taylor series expansion and finally show that the pricing kernel is a linear combination of the consumption growth and its higher moments. One difficulty with the Taylor expansion is the determination of the order at which the expansion should be truncated. Some studies such as Bansal et al. (1993) let the data determine the point of truncation. The difficulty with this approach is a loss of power; in allowing the data to guide the specification of the pricing kernel, the researcher risks over fitting the data. Furthermore, the economic interpretation of the resulting kernel is open to question. Therefore, I follow a more powerful approach in this paper that is to allow preference theory to guide the truncation. Specifically, I apply Taylor expansion on the marginal utility of consumption at consumption level in the prior period and truncate at order three, which lead to the pricing kernel is a function of consumption growth from power of one to the power of three. Put differently, my framework allows me to estimate representative agent's preferences parameters including risk aversion, risk prudence, and risk temperance (see Kimball (1993), Chiu (2005), and Denuit and Eeckhoudt (2010)).

The idea that changing volatility of consumption or aggregate cash flows can affect asset prices and equity premia has a long-standing place in the asset pricing literature. Early work investigating this volatility channel includes Barsky (1986), Abel (1988), Giovannini (1989), Kandel et al. (1989), Kandel and Stambaugh (1990), and Gennotte and Marsh (1993). More recently, Bansal and Yaron (2004) have taken this idea to a model of recursive preferences of the type explored by Epstein and Zin (1989) and Weil (1989), showing that a reduction in consumption volatility can raise asset prices if the intertemporal elasticity of substitution is greater than unity. Bansal and Lundblad (2002), Bansal et al. (2005), and Duffee (2005) further explore theoretical and empirical links between second moments of consumption growth, equity valuation ratios, and returns. Besides, Lettau et al. (2008) estimate a two-state regime switching model for the volatility and mean of consumption growth, and find evidence of a shift to substantially lower consumption volatility at the beginning of the 1990s. Therefore, I apply Markov-switching model on the consumption dynamics in this paper.

To summarize, I propose and estimate through Bayesian methods a flexible parametric multi-factor asset pricing model in which the importance of higher moments of consumption risk is highlighted. Moreover, the dynamics of the consumption growth are modeled as a latent regime switching process such that it is restricted by allowing the dynamics of the consumption growth to effectively explain the cross-section of U.S. stock returns. It is worth to mentioning that this framework – different from current studies – allows me to simultaneously estimate preferences parameters for higher moments of consumption risk under utility-free setting and parameters that govern consumption dynamics such that the consumption growth dynamics are consistent with the cross-section of stock returns. Ideally, the empirical results should show that the newly proposed model framework and estimation algorithm are important in the sense that this paper's setup is able to explain the cross-section of stock returns by incorporating the higher moments of consumption growth into the stochastic discount factor. More importantly, the estimated preferences parameters including risk aversion, risk prudence and risk temperance are at reasonable level and the estimated consumption dynamics are also compatible with the real data.

The rest of the paper is organized as follows. Section 4.2 describes model specification and derive the stochastic discount factor by incorporating higher moments of consumption risk. Section 4.3 introduces the details of my estimation method, which is operated under Bayesian paradigm by combining Particle Gibbs Sampler with Ancestor Sampling. Then in Section 4.4, I describe the details of the implementation of my estimation algorithm and data sample used in this paper. Section 4.5 will present the main empirical results. Section 4.6 concludes the paper.

4.2 Model Specification

This paper attempts to highlight the importance of the higher moments of consumption risk in pricing assets cross sectionally. In this section, I mainly focus on deriving an explicit expression of the stochastic discount factor that incorporates the information of the higher moments of consumption growth by extending the classical consumption-based capital asset pricing model (CCAPM) framework (see, e.g., Lucas Jr (1978) and Breeden (1979)).

4.2.1 Agent's Problem

To develop a specific pricing kernel by incorporating the information of higher moments of consumption growth, I start with the classical consumption-based capital asset pricing model (CCAPM) framework. I assume there is a representative agent in the economy who maxmizes her lifetime utility. Specifically, the maximization problem of this agent is given by

$$Max_{\xi} E_t[\sum_{\tau=0}^{\infty} \beta^{\tau} U(C_{t+\tau})]$$
$$s.t.$$
$$C_t = e_t - \xi P_t$$
$$C_{t+1} = e_{t+1} + \xi x_{t+1}$$

where β is the subjective discount factor, C_t is the consumption at time t, P_t is the price of the asset at time t (consumption goods or a claim on it), e_t is the endowment, and x_{t+1} is the payoff of investing on the asset at time $t+1$. By solving the above described representative agent's problem, the general Euler equation has the following form

$$E_t[\beta \frac{U'(C_{t+1})}{U'(C_t)} R_{i,t+1}] = 1, \quad i = 1, 2, ..., N \tag{4.2.1}$$

where $R_{i,t+1}$ is the gross return of asset i, and equation (4.2.1) applies to all assets. Instead of using the gross stock return, the equation (4.2.1) can be rewritten as

$$E_t[\frac{U'(C_{t+1})}{U'(C_t)}(R_{i,t+1} - R_f)] = 0 \tag{4.2.2}$$

where R_f is the gross risk free rate and hence $R_{i,t+1} - R_f$ in the equation (4.2.2) is the excess return of stock i. In addition, the investor's intertemporal marginal rate of substitution $\frac{U'(C_{t+1})}{U'(C_t)}$ can be interpreted as the stochastic discount factor in the literature of asset pricing.

4.2.1.1 Stochastic Discount Factor with Higher Moments

When considering the importance of the higher moments risk, current studies usually incorporate the higher moment of market return into stochastic discount factor directly (e.g., Dittmar (2002)). Although this assumption makes things easy, but it less appealing from the standpoint of economic theory. In this project, I concentrate on the higher moment of consumption risk. The assumption of the existence of a representative agent allows the pricing kernel to be expressed as a function of aggregate consumption, but a suitable representation for the agent's utility function is unknown. A large body of literature investigates standard choices for agent's utility and finds that the data imply unrealistic assumptions about investors' risk aversion or the risk-less rate (e.g., Mehra and Prescott (1985) and Weil (1989)). Different from these studies, I do not specify the exact utility function form and instead I express the pricing kernel as a nonlinear function of consumption growth. It is worth to mentioning that my setup is more flexible than the model with a concrete utility function. Specifically, I apply taylor expansion to $U'(C_{t+1})$ at C_t and truncate at order three, which is guided by the preference theory, making the resulting kernel has meaningful economic interpretation.

By implementing Taylor expansion on $U'(C_{t+1})$ at C_t, I get the following expression of the first order derivative of the agent's utility function

$$U'(C_{t+1}) \simeq$$
$$U'(C_t) + U''(C_t)(C_{t+1} - C_t) + \frac{1}{2}U'''(C_t)(C_{t+1} - C_t)^2 + \frac{1}{6}U''''(C_t)(C_{t+1} - C_t)^3$$
$$= U'(C_t) + C_tU''(C_t)(\frac{C_{t+1}}{C_t} - 1) + \frac{1}{2}C_t^2U'''(C_t)(\frac{C_{t+1}}{C_t} - 1)^2 + \frac{1}{6}C_t^3U''''(C_t)(\frac{C_{t+1}}{C_t} - 1)^3$$

Rewriting the above equation, the stochastic discount factor $\frac{U'(C_{t+1})}{U'(C_t)}$ is given by

$$\frac{U'(C_{t+1})}{U'(C_t)} \simeq$$
$$1 + \frac{C_tU''(C_t)}{U'(C_t)}(\frac{C_{t+1}}{C_t} - 1) + \frac{1}{2}\frac{C_t^2U'''(C_t)}{U'(C_t)}(\frac{C_{t+1}}{C_t} - 1)^2 + \frac{1}{6}\frac{C_t^3U''''(C_t)}{U'(C_t)}(\frac{C_{t+1}}{C_t} - 1)^3 \tag{4.2.3}$$

I denote the log consumption growth as $\triangle c_{t+1}$ and it can be represented with $\triangle c_{t+1} = log(C_{t+1}/C_t)$, and then the simple consumption growth is given by $\frac{C_{t+1}}{C_t} = e^{\triangle c_{t+1}} \approx 1 + \triangle c_{t+1}$. Plug this simple consumption growth $\frac{C_{t+1}}{C_t}$ into the above equation (4.2.3), the stochastic discount factor can be represented as a function of higher moments of consumption growth

$$\frac{U'(C_{t+1})}{U'(C_t)} \simeq 1 + \frac{C_tU''(C_t)}{U'(C_t)}\triangle c_{t+1} + \frac{1}{2}\frac{C_t^2U'''(C_t)}{U'(C_t)}(\triangle c_{t+1})^2 + \frac{1}{6}\frac{C_t^3U''''(C_t)}{U'(C_t)}(\triangle c_{t+1})^3 \tag{4.2.4}$$

One purpose of the paper is to estimate the preferences parameters for the higher moments of consumption risk, and therefore, I further follow convention and define relative risk aversion (RA), relative prudence (RP), and relative temperance (RT) as follows

$$RA \equiv -\frac{C_tU''(C_t)}{U'(C_t)}, \quad RP \equiv -\frac{C_tU'''(C_t)}{U''(C_t)}, \quad RT \equiv -\frac{C_tU''''(C_t)}{U'''(C_t)}$$

Combining the above equations (4.2.1) and (4.2.4), then the stochastic discount factor (SDF), denoted as M_{t+1}, can be represented as

$$M_{t+1} = \beta \frac{U'(C_{t+1})}{U'(C_t)}$$
$$= \beta[1 - RA \cdot \triangle c_{t+1} + \frac{1}{2} RA \cdot RP \cdot (\triangle c_{t+1})^2 - \frac{1}{6} RA \cdot RP \cdot RT \cdot (\triangle c_{t+1})^3] \quad (4.2.5)$$

Or equivalently, SDF can be expressed by

$$M_{t+1} = \alpha_0 + \alpha_1 \cdot \triangle c_{t+1} + \alpha_2 \cdot (\triangle c_{t+1})^2 + \alpha_3 \cdot (\triangle c_{t+1})^3 \quad (4.2.6)$$

where alphas are given by

$$\alpha_0 = \beta$$
$$\alpha_1 = -\beta \cdot RA$$
$$\alpha_2 = \frac{1}{2} \beta \cdot RA \cdot RP$$
$$\alpha_3 = -\frac{1}{6} \beta \cdot RA \cdot RP \cdot RT$$

With the above SDF, Euler equation (4.2.1) can be re-written as

$$E_t[M_{t+1} R_{i,t+1}] = 1, \quad i = 1, 2, ..., N \quad (4.2.7)$$

To highlight the importance of higher moments, the classical literature usually estimates the above described model with GMM method by employing moments implied by Euler equation. But, GMM only works when consumption growth is observable. In this project, I also interested in the dynamics of consumption growth and hence I assume the consumption growth is a latent variable, making it impossible to apply standard GMM estimation. I put forward a novel estimation procedure in the following section to solve this issue.

4.2.2 Consumption Growth Dynamics

Obviously, the above Euler equation (4.2.7) puts constraints on the dynamics of consumption growth. On the other hand, the idea that changing mean and volatility of consumption or aggregate cash flows can affect asset prices and equity premia has a long-standing place in the asset pricing literature (see Kandel and Stambaugh (1990), Bansal and Yaron (2004), Lettau et al. (2008), among others), and therefore, to investigate the dynamics of consumption growth, I adopt the widely used assumption on consumption growth, i.e., assuming the distribution of consumption growth has two regimes and it satisfies

$$\triangle c_t = \mu_{s_t} + \sigma_{s_t}\epsilon_t \tag{4.2.8}$$

where ϵ_t is the iid error term with mean at zero and standard deviation at one, and s_t follows a two-state first order Markov process with transition probability matrix P.

$$P(i,j) = Pr(S_{t+1} = j|S_t = i) = p_{i,j}, \quad i,\ j \in \{1,2\} \tag{4.2.9}$$

Let $\theta = (\alpha_0, \alpha_1, \alpha_2, \alpha_3, \mu_1, \mu_2, \sigma_1, \sigma_2, P)$ be the set of parameters of the above described model[1]. In this paper, I am interested in estimating θ without adding assumptions on the joint distribution of consumption growth and asset returns and without assuming the concrete form of agents' utility function. To do this, I propose a new estimation procedure based on Bayesian estimation technique, which is explained with details in the following section.

4.3 The Econometric Estimation Approach

Under the theoretical framework introduced in the Section 4.2, the main challenge to estimate parameters θ is the consumption growth is latent, making the standard GMM technique is not suitable for the above model. Moreover, the above setup requires to estimate agent's preferences parameters and consumption dynamics simultaneously, and in the meanwhile, it also constraints the Euler equation must be satisfied for a large set of assets. To solve this issue, I draw insights from bayesian estimation method and put forward a new estimation procedure. In this section, I explain the details of this paper's estimation method.

4.3.1 State Space Representation

Given I do not assume the joint distribution of the consumption growth and stock return, and hence the above model does not generate an explicit form of stock return as a function of consumption growth risk. However, the above model specification can be re-written into state space representation, which includes the measurement equation and the transition equation. For this paper's purpose, the measurement equation is the above Euler equation, and the transition equation is the dynamic of the consumption growth. To easily explain this paper's estimation

[1] With regime switching assumption on the consumption growth, preferences parameters of $\alpha_i,\ i = 1,2,3$ may also related with regimes, i.e., depend on s_t.

method, I temporary ignore the above specific notations and re-write the above model into a general state space representation. I will connect the following general estimation framework with this paper's notations in the next section. Rewriting Euler equation as

$$E[h(y_{t+1}, x_{t+1}, \theta)|I_t] = 0 \tag{4.3.1}$$

where $y = (y_1, ..., y_T)$ is observable variable, $x = (x_1, ..., x_T)$ is latent variable, and θ is the parameter of interest. I_t denotes the information set at time t. Corresponding to my case, y may includes a variety of security returns while x may be represented by consumption growth. Similar to the GMM estimation technique, I consider the unconditional form of the above Euler equation (4.3.1)

$$E[g(y_{t+1}, x_{t+1}, \theta)] = 0 \tag{4.3.2}$$

where g may be expressed by $g(y_{t+1}, x_{t+1}, \theta) = h(y_{t+1}, x_{t+1}, \theta) \otimes V(y_t, x_t)$, and $V(y_t, x_t)$ is a set of instruments that are I_t measurable. In terms of selecting instruments, it is often guided by economic theory.

Align with the above described general state space representation, the model in Section 4.2 can be expressed in a general form as

$$E[g(y_t, x_t, \theta)] = 0 \tag{4.3.3}$$

$$x_t = \mu_{s_t} + \sigma_{s_t}\epsilon_t \tag{4.3.4}$$

4.3.2 Bayesian Paradigm

As explained in the previous section, I am interested in parameters both in the moment conditions (equation (4.3.3)) and in the transition equation (equation (4.3.4)). To estimate these two types of parameters simultaneously, I resort to bayesian estimation method. To apply bayesian based estimation technique into the above model, I need to fix the joint distribution of the observable variable, the latent variable and the interest parameters. Specifically,

$$p(y, x, s, \theta) = p(y|x, s, \theta)p(x, s|\theta)p(\theta) \tag{4.3.5}$$

However, the measurement density $p(y|x, s, \theta)$ is unobservable but instead we know moment conditions $E[g(y_t, x_t, \theta)] = 0$. Fortunately, the theoretical work of Gallant (2015), Gallant (2016), and Gallant et al. (2017) show that we can replace $p(y|x, s, \theta)$ with a transform of moment conditions like $\varphi(Z(y, x, \theta))$ for the purpose of bayesian inference. $Z(y, x, \theta)$ is a normalized sample moments.

4.3.2.1 Estimation Details

Under this paper's model setup, there are two latent variables, x and s, and the measurement density does not represented with a closed form. This setup is different from the classical state space model in which only one latent transition equation. And therefore, to align with the bayesian paradigm, I resort to Particle Gibbs method to estimate the above described model. Particle Gibbs technique is based on an Sequentially Monte Carlo (SMC) sampler, akin to a standard particle filtering, but with the difference that one particle trajectory is specified a priori. This priori is served as a reference trajectory, which keeps intact throughout the sampling procedure. Unfortunately, this procedure has been recognized that the mixing properties of this kernel can be very poor due to path degeneracy (see e.g., Lindsten and Schön (2012) and Chopin et al. (2015)).

To deal with the issue of degeneracy of particle Gibbs method, I adopt the newly proposed ancestor sampling algorithm. In general, my estimation method is a combination of Particle Gibbs sampler of Andrieu et al. (2010), ancestor sampling approach of Lindsten and Schön (2012) and Lindsten et al. (2014) as well as the idea of partially deterministic particle filtering method of Fearnhead et al. (1998) and Kim (2015). It is worth mentioning that the theoretical foundation of my estimation algorithm is based on the work of Gallant et al. (2017).

To jointly estimate the two latent variables, x and s and the unknown parameters θ, I set down the following posterior density

$$p(x_{1:T}, s_{1:T}, \theta|y_{1:T}) \propto \varphi[Z(y_{1:T}, x_{1:T}, \theta)] \prod_{t=1}^{T} p(x_t|s_t, \theta)p(s_t|s_{t-1}, \theta)p(\theta) \tag{4.3.6}$$

where Z is a normalized function of sample moments and φ is the standard normal distribution inspired by the work such as Hansen (1982) and Gallant and White (1988). Specifically, Z and φ are given by

$$Z = (\Omega(y, x, \theta))^{-1/2} g_T(y, x, \theta) \tag{4.3.7}$$

$$g_T(y, x, \theta) = \frac{1}{\sqrt{T}} \sum_{t=1}^{T} g(y_t, x_t, \theta) \tag{4.3.8}$$

$$\Omega(y, x, \theta) = \frac{1}{T} \sum_{t=1}^{T} [g(y_t, x_t, \theta) - \frac{1}{\sqrt{T}} g_T(y, x, \theta)][g(y_t, x_t, \theta) - \frac{1}{\sqrt{T}} g_T(y, x, \theta)]' \tag{4.3.9}$$

$$\varphi(Z(y_{1:T}, x_{1:T}, \theta)) = (2\pi)^{M/2} exp\{-\frac{1}{2} g_T(y_{1:T}, x_{1:T}, \theta)'(\Omega(y_{1:T}, x_{1:T}, \theta))^{-1} g_T(y_{1:T}, x_{1:T}, \theta)\} \tag{4.3.10}$$

As above mentioned, I employ particle Gibbs with ancestor sampling to avoid degeneracy and to obtain the mixing property of regular Markov Chain Monte Carlo method in making inference about $(x_{1:T}, s_{1:T}, \theta)$. In doing so, I follow the convention of literature on ancestor sampling like Lindsten et al. (2014) and first introduce auxiliary indices to help me explain my estimation procedures clearly. Denote a_t^i as the index for the ancestor particle of $\{x_t^i, s_t^i\}$ at time t-1 and $a_t^i \in \{1, ..., N\}$. Then, the joint density of latent variables and auxiliary indices can be represented as

$$\phi(X_{1:T}, S_{1:T}, A_{2:T}|\theta) = \prod_{i=1}^{N} q(x_1^i, s_1^i) \prod_{t=2}^{T} \prod_{i=1}^{N} M_{\theta,t}(x_t^i, s_t^i, a_t^i) \tag{4.3.11}$$

where $X_{1:T} = \{x_{1:T}^i\}_{i=1}^N$, $S_{1:T} = \{s_{1:T}^i\}_{i=1}^N$, $A_{2:T} = \{a_{2:T}^i\}_{i=1}^N$, and the proposal kernel $M_{\theta,t}$ is given by

$$M_{\theta,t}(x_t^i, s_t^i, a_t^i) = \hat{\omega}_{t-1}^i q(x_t^i, s_t^i | x_{1:t-1}^{a_t^i}, s_{1:t-1}^{a_t^i}) \tag{4.3.12}$$

$$\omega_t^i = \frac{\varphi(Z(y_{1:t}, x_{1:t}^i, s_{1:t}^i, \theta)) p(x_t^i | s_t^i, \theta) p(s_t^i | s_{t-1}^i, \theta)}{q(x_t^i, s_t^i | x_{1:t-1}^{a_t^i}, s_{1:t-1}^{a_t^i})} \tag{4.3.13}$$

$$\hat{\omega}_t^i = \frac{\omega_t^i}{\sum_j \omega_t^j} \tag{4.3.14}$$

where $q(\cdot)$ is the proposal importance densities. In addition, I let $k \in \{1, ..., N\}$ be the index for a fixed reference particle trajectory. For example, the particle trajectory $(x_{1:T}^k, s_{1:T}^k)$ is the ancestral path of the particle (x_T^k, s_T^k). Then, I can write

$$x_{1:T}^k = x_{1:T}^{b_{1:T}} = (x_1^{b_1}, ..., x_T^{b_T}) \tag{4.3.15}$$

$$s_{1:T}^k = s_{1:T}^{b_{1:T}} = (s_1^{b_1}, ..., s_T^{b_T}) \tag{4.3.16}$$

where the indices $b_{1:T}$ are given recursively by the ancestor indices, that is, $b_T = k$ and $b_t = a_{t+1}^{b_{t+1}}$. In fact, the variable b_t plays a role to locate the each particle component of the reference trajectory in the generated particle swarm.

With all above auxiliary indices $(a_{2:T}^i, k, b_{1:T})$, I am able to derive conditional density of all other particle trajectory given a reference trajectory $\{x_{1:T}^{b_{1:T}}, s_{1:T}^{b_{1:T}}\}$ as follows:

$$\phi(X_{1:T}^{-b_{1:T}}, S_{1:T}^{-b_{1:T}}, A_{2:T}^{-b_{2:T}} | x_{1:T}^{b_{1:T}}, s_{1:T}^{b_{1:T}}, b_{1:T}, \theta) = \prod_{i \neq b_1}^{N} q(x_1^i, s_1^i) \prod_{t=2}^{T} \prod_{i \neq b_t}^{N} M_{\theta,t}(x_t^i, s_t^i, a_t^i) \tag{4.3.17}$$

where $X_{1:T}^{-b_{1:T}}$ and $S_{1:T}^{-b_{1:T}}$ represent all the particles except the reference trajectory. Follow the work of Andrieu et al. (2010), I then define the extended target density as follows:

$$\phi(X_{1:T}, S_{1:T}, A_{2:T}, k, \theta) = \frac{1}{N^T} p(x_{1:T}^{b_{1:T}}, s_{1:T}^{b_{1:T}}, b_{1:T}, \theta | y_{1:T}) \prod_{i \neq b_1}^{N} q(x_1^i, s_1^i)$$
$$\times \prod_{t=2}^{T} \prod_{i \neq b_t}^{N} M_{\theta,t}(x_t^i, s_t^i, a_t^i) \quad (4.3.18)$$

With the above extended target density, and the fact that my transition equation only depends on the current latent state s_t (first-order markov chain), I follow Lindsten et al. (2014) to show that

$$\varphi(b_{t-1}|X_{1:t-1}, S_{1:t-1}, A_{2:t-1}, x_{t:T}^{b_{t:T}}, s_{t:T}^{b_{t:T}}, b_{t:T}, \theta) \propto \frac{p(x_{1:T}^{b_{1:T}}, s_{1:T}^{b_{1:T}} | y_{1:T}, \theta)}{p(x_{1:t-1}^{b_{1:t-1}}, s_{1:t-1}^{b_{1:t-1}} | y_{1:t-1}, \theta)} \hat{\omega}_{t-1}^{b_{t-1}} \quad (4.3.19)$$

$$\propto p(x_t^{b_t} | s_t^{b_t}, \theta) p(s_t^{b_t} | s_{t-1}^{b_{t-1}}, \theta) \times \hat{\omega}_{t-1}^{b_{t-1}} \quad (4.3.20)$$

Given the above density, I draw $b_{t-1} \in \{1, ..., N\}$ with the following probability

$$\bar{\omega}_{t-1|T}^i = p(x_t^{b_t} | s_t^{b_t}, \theta) p(s_t^{b_t} | s_{t-1}^i, \theta) \times \hat{\omega}_{t-1}^i \quad (4.3.21)$$

$$\hat{\bar{\omega}}_{t-1|T}^i = \frac{\bar{\omega}_{t-1|T}^i}{\sum_j \bar{\omega}_{t-1|T}^j} \quad (4.3.22)$$

Unlike the general particle Gibbs sampler which makes MCMC iteration relies on a fixed particular reference trajectory, the particle Gibbs with ancestor sampling allows each component in the reference particle trajectory to update sequentially by drawing the index b_{t-1} for each period. Based on the above extended target density and the results of Andrieu et al. (2010), I can also prove that

$$\varphi(k | X_{1:T}, S_{1:T}, A_{2:T}, \theta) \propto \omega_T^k \quad (4.3.23)$$

To update reference trajectory for each iteration, I am able to easily draw $k \in \{1, ..., N\}$ based on above density.

Regarding to this paper's case, it only has limited number of states/regimes s_t, and to fully exploit all past particle paths related with s_t, I adopt the idea of the partially deterministic particle filtering approach of Fearnhead et al. (1998), Nemeth et al. (2015) and Kim (2015) and assign value of s_t^i deterministically.[1] Then I generate N particles by proposal importance density of x_t for each value of $s_t \in \{1, 2\}$. Given s_t is deterministically assigned, then the proposal importance density can be expressed as follows:

$$q(x_t, s_t|x_{1:t-1}, s_{1:t-1}) \propto q(x_t|x_{1:t-1}, s_{1:t}) = q(x_t|s_t) \tag{4.3.24}$$

Finally, for all other parameters θ, I resort to Metropolis-Hastings algorithm to draw them because the above model setup does not generate a closed form of measurement density.

4.3.3 Summary of Estimation Algorithm

Based on the above detailed analysis, to target $p(x_{1:T}, s_{1:T}, \theta|y_{1:T})$, my estimation algorithm can be proceeded as follows:

- Step 1 Start
  - Arbitrarily choose θ^0 and draw a reference trajectory $\{x_{1:T}^k, s_{1:T}^k\}$ from particle swarm $\{X_{1:T}, S_{1:T}\}$
- Step 2 Particle Gibbs (PG) - Ancestor Sampling (AS)
  - Initialization
    * Draw $\{x_1^i, s_1^i\}_{i=1}^{2N}$ from $q(x_1, s_1)$ except $\{x_1^m, s_1^m\}$, where $m = s_1^{b_1} N$, and replace $\{x_1^m, s_1^m\}$ with $\{x_1^{b_1}, s_1^{b_1}\}$
    * Choose T_0 to be the smallest t required to calculate $g_t(y_{1:t}, x_{1:t}, \theta)$ and $\Omega(y_{1:t}, x_{1:t}, \theta)$, and draw $\{x_{1:T_0}^i, s_{1:T_0}^i\}_{i=1}^{2N}$ by repeating T_0 times of the above step
    * Compute importance weights $\omega_{T_0}^i = \frac{p(x_{T_0}^i|s_{T_0}^i,\theta)p(s_{T_0}^i,\theta)}{q(x_{T_0}^i,s_{T_0}^i)}$, and save the normalized weights $\{\hat{\omega}_{T_0}^i = \frac{\omega_{T_0}^i}{\sum_j \omega_{T_0}^j}\}_{i=1}^{2N}$
  - Re-sampling and Importance sampling (Iterate for $t = T_0 + 1, ..., T$)
    * Re-sampling by drawing $\{\hat{x}_{t-1}^i, \hat{s}_{t-1}^i\}_{i=1}^N$ from $\{x_{t-1}^i, s_{t-1}^i\}_{i=1}^{2N}$ with probability $\{\hat{\omega}_{t-1}^i\}_{i=1}^{2N}$ and replicate 2 times (2 regimes) to obtain $\{\hat{x}_{t-1}^i, \hat{s}_{t-1}^i\}_{i=1}^{2N}$. In the meanwhile, given our auxiliary indices a_t^i, this step is equivalent to draw $\{a_t^i\}_{i=1}^N$ with probability

[1] To deterministically assign value to s_t^i, I do as follows. For example, given there are two regimes, for the first regime, I assign $s_t^i = 1$ for all first N particles, while for the second regime, I assign $s_t^i = 2$ for all second N particles.

$\{\hat{\omega}^i_{t-1}\}^{2N}_{i=1}$ and replicate 2 times to get $\{a^i_t\}^{2N}_{i=1}$ (i.e., $(\hat{x}^i_{1:t-1}, \hat{s}^i_{1:t-1}) = (x^{a^i_t}_{1:t-1}, s^{a^i_t}_{1:t-1})$)

  * Draw $\{x^i_t, s^i_t\}^{2N}_{i=1}$ from $q(x^i_t, s^i_t|x^{a^i_t}_{1:t-1}, s^{a^i_t}_{1:t-1})$ except $\{x^m_t, s^m_t\}$ and $m = s^{b_t}_t N$. Replace $\{x^m_t, s^m_t\}$ with $\{x^{b_t}_t, s^{b_t}_t\}$
  * Compute weights for ancestor sampling, $\bar{\omega}^i_{t-1|T} = p(x^{b_t}_t|s^{b_t}_t, \theta)p(s^{b_t}_t|s^i_{t-1}, \theta)\omega^i_{t-1}$, and then save the normalized weights $\hat{\bar{\omega}}^i_{t-1|T} = \frac{\bar{\omega}^i_{t-1|T}}{\sum_j \bar{\omega}^j_{t-1|T}}$
  * Ancestor sampling by drawing b_{t-1} with probability $\hat{\bar{\omega}}^i_{t-1|T}$, i.e., draw b_{t-1} with $p(b_{t-1} = i) \propto \hat{\bar{\omega}}^i_{t-1|T}$, and set $\{a^m_t = b_{t-1}\}$
  * Update new particle trajectories as $\{x^i_{1:t}, s^i_{1:t}\}^{2N}_{i=1} = \{x^{a^i_t}_{1:t-1}, s^{a^i_t}_{1:t-1}, x^i_t, s^i_t\}^{2N}_{i=1}$
  * Update new weights $\omega^i_t = \frac{\varphi(Z(y_{1:t}, x^i_{1:t}, \theta))p(x^i_t|s^i_t, \theta)p(s^i_t|s^{a^i_t}_{t-1}, \theta)}{q(x^i_t, s^i_t|x^{a^i_t}_{1:t-1}, s^{a^i_t}_{1:t-1})}$ and compute normalized weights $\hat{\omega}^i_t = \frac{\omega^i_t}{\sum_j \omega^j_t}$ for $i \in \{1, ..., 2N\}$

- Then set $X_{1:T} = \{X^{-b_{1:T}}_{1:T}, x^{b_{1:T}}_{1:T}\}$, $S_{1:T} = \{S^{-b_{1:T}}_{1:T}, s^{b_{1:T}}_{1:T}\}$, and $A_{2:T} = \{A^{-b_{2:T}}_{2:T}, b_{2:T-1}\}$

- Step 3 Update reference trajectory
  - Draw $k \in \{1, ..., 2N\}$ from $\varphi(k|X_{1:T}, S_{1:T}, A_{2:T}, \theta)$, that is to draw $k \in \{1, ..., 2N\}$ with probability $\hat{\omega}^k_T$. In other wards, draw k with $p(k = i) \propto \hat{\omega}^i_T$. Then set $\{x^{b_{1:T}}_{1:T}, s^{b_{1:T}}_{1:T}\} = \{x^k_{1:T}, s^k_{1:T}\}$

- Step 4 Draw other parameters θ (Metropolis Step)
  - Start with $i = 1$ and $\theta^i = \theta^0$
  - Propose: Draw θ^{new} from $q(\theta|\theta^i)$
  - Compute acceptance probability: $\alpha_{MH} = min(\frac{p(y_{1:T}, x^{b_{1:T}}_{1:T}, s^{b_{1:T}}_{1:T}, \theta^{new})q(\theta^i|\theta^{new})}{p(y_{1:T}, x^{b_{1:T}}_{1:T}, s^{b_{1:T}}_{1:T}, \theta^i)q(\theta^{new}|\theta^i)}, 1)$, and set $\theta^{i+1} = \theta^{new}$ with probability α_{MH}
  - Repeat Metropolis steps Q times

- Step 5 Repeat Steps 2-4 R times to get MCMC chain $\{x^r_{1:T}, s^r_{1:T}, \theta^r\}^R_{r=1}$

4.4 Implementation and Data

4.4.1 Implementation of Estimation

The estimation procedure proposed in Section 4.3 is adapted to the general state space representation. For this paper's setup, I explain in this section the details of the implementation of the above proposed estimation method. The crucial step in the above mentioned estimation algorithm is to construct the joint density function of interest parameters and observable variables. Based on the theoretical work of Gallant et al. (2017), I construct the joint density function as follows.

I first compute Euler equation errors with the following formula

$$e_t(M_{t+1}, R_{t+1}, B_{t+1}) = 1 - M_{t+1} \begin{pmatrix} R_{t+1} \\ B_{t+1} \end{pmatrix} \tag{4.4.1}$$

where M_{t+1} is the stochastic discount factor in Section 4.2, R_{t+1} is a vector of asset returns, and B_{t+1} is the return on the thirty-day treasury bill. In terms of selecting the informed instruments, V_t, I follow the literature with the GMM estimation and choose the one-period lag of the asset returns, lagged consumption growth, as well as a constant as instruments. Specifically, the instrument vector V_t is given by

$$V_t = \begin{pmatrix} R_t - 1 \\ B_t - 1 \\ \triangle c_t \\ 1 \end{pmatrix}$$

Then, the constructed moment functions can be represented by

$$m_t(M_{t+1}, R_{t+1}, B_{t+1}, R_t, B_t, \triangle c_t) = V_t \otimes e_t(M_{t+1}, R_{t+1}, B_{t+1}) \tag{4.4.2}$$

Following Gallant and Hong (2007) I further assume that $(M_{t+1}R_{t+1}, M_{t+1}B_{t+1})$ has a factor structure, and then the joint density function $g(y, x, \theta)$ in equation 4.3.3 can be explicitly represented as a function of the above constructed moment function m_t (equation (4.4.2)). In particular, I assume there is one error common to all elements of M_tR_t, one error common to all elements of M_tB_t, and the number of idiosyncratic errors is the summation of the number of elements in M_tR_t and M_tB_t. Put differently, each element of M_tR_t and M_tB_t has an idiosyncratic error. I denote this matrix by Σ_e. A set of orthogonal eigenvectors U_e for Σ_e are easy to construct and can be used to diagonalize Σ_e. Similarly, denote Σ_v for instruments V_t and its orthogonalized eigenvectors are labeled by U_v. Note that U_v has one extra block for $\triangle c_t$ and a one appended to the southeast corner compared to the matrix U_e. Under the above assumptions, the equation (4.3.8) in Section 4.3.2.1 is given by

$$g_T(y,x,\theta) = \frac{1}{\sqrt{(T)}}(U_v \otimes U_e)' m_t(M_{t+1}, R_{t+1}, B_{t+1}, R_t, B_t, \triangle c_t) \tag{4.4.3}$$

where $y_{t+1} = (R_{t+1}, B_{t+1}, R_t, B_t, \triangle c_t)$, x_{t+1} are the latent variables of $\triangle c_{t+1}$ and s_{t+1}, and θ is the set of preferences parameters and the paramters governing the consumption growth $\triangle c_{t+1}$ and states s_{t+1} dynamics. Then, with the expression of $g_T(y,x,\theta)$ in the equation (4.4.3), the above θ can be estimated by following the steps introduced in section 4.3.2.1.

4.4.2 Data

This paper is interested in identifying preferences parameters as well as parameters governing consumption dynamics simultaneously such that the consumption dynamics are compatible with the cross-sectional variation of stock returns. For this purpose, I consider the widely used Fama-French 25 portfolios data, denoted by $R_{t+1} = (R_{1,t+1}, ..., R_{25,t+1})'$ as well as the thirty-day treasury bill data, denoted by B_{t+1}. The stock data and the treasury bill data are collected from Kenneth French's website.[1]. Besides, the monthly aggregate consumption expenditures and the data of the consumption expenditures for nondurable goods and for services are downloaded from the Federal Reserve Bank of St. Louis.[2] For calculating consumption per capita C_t, I collect U.S. population data from the United States Census Bureau.[3] The monthly data covers the period from January 1959 to July 2018.

4.5 Empirical Results

In this section, I will show the main results of the paper. Given I am still working on the empirical part, and hence I will show the expected results. In particular, to emphasize the importance of higher moments of consumption risk in pricing asset returns in the cross section, I will report the main results under two scernarios. Under the first case, I will consider the normal SDF, i.e., the SDF without higher moments. Then, in the second case, I will apply the above newly proposed

[1] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[2] https://fred.stlouisfed.org/
[3] https://www.census.gov/programs-surveys/popest/data/data-sets.html

estimation approach to the SDF including the higher moments of consumption growth.

4.5.1 SDF Without Higher Moments

To highligt the importance of the higher moments of consumption risk in pricing cross-section asset returns, I first apply the above mentioned estimation approach to the real data by only considering the normal SDF, i.e., the SDF without higher moments of consumption growth. Ideally, as expected, the only macroeconomic consumption grwoth factor is hardly explain the cross-sectional variation of asset returns, which is also consistent with the previous findings in the literature. Although I estimate the risk aversion parameter and consumption dynamics simultaneouly, the risk aversion parameter will ideally be at an unreasonble high value to make the setup to be able to effectively explain the cross-sectional dynamics of asset returns.[1]

4.5.2 SDF With Higher Moments

One contribution of this paper is that it extends the canonical consumption-based CAPM by incorporating the higher moments of consumption growth into the stochastic discount factor under a utility-free framework. Therefore, to support the aforementioned novel point, I should observe that the whole model setup cannot explain the cross-sectional variation of asset returns without considering the higher moments of consumption growth, which has been shown in the above section. More importantly, I should also show that my model framework and estimation apporoach are able to generate reasonable preferences parameters as well as consumption dynamics when explaining the cross section asset returns by including higher moments of conumption growth into the stochastic discount factor.

4.6 Conclusion

In this paper, I investigate the importance of higher moments of consumption risk in pricing cross-section asset returns. Under the canonical consumption-based asset pricing model framework, I extend the current studies by deriving a stochastic discount factor such that it incorporates the higher moments of consumption growth. More importantly, the newly derived stochastic discount factor does not

[1] Notice that there is only one preferences parameter, i.e., risk aversion, when I do not consider the higher moments of consumption growth.

rely on the specific utility function. Besides, in order to analyze the dynamics of consumption growth, I follow the literature and assume that the distribution of consumption growth satisfies a two-state regime switching process. It is worth to mentioning that the consumption growth itself is modeled as a latent factor, which is the key difference with the current studies, making the classical GMM estimation approach cannot be applied under this paper's model setup when estimating the representative agent's preferences parameters.

To solve the above mentioned issue, I propose a new Bayesian estimation algorithm which allows me to simultaneously estimate preference parameters associated with higher moments of conumption risk and parameters that related to consumption dynamics such that the consumption dynamics are consistent with the cross sectional variation of asset returns. Then, I apply my model and estimation approach to the Fama and French 25 portfolios. I consider the monthly consumpiton data ranging from January 1959 to July 2018, and the empirical results ideally should show that the preferences paramters including risk aversion, risk prudence and risk temperance and the parameters that govern the consumption dynamics are all at reasonable levels when explaining the cross-section portfolios' returns. Overall, the results say that the higher moments of consumption risk are important and able to explain the cross sectional variation of asset returns under reasonable risk preferences levels when estimating preferences parameters and consumption dynamics simultaneously with a newly proposed Bayesian estimation algorithm.

Chapter 5

Conclusion

This thesis empirically investigates the importance of higher moments risks in asset pricing. In Chapter 2, I focus on exploring the risk premia associated with skewness risk. I extend existing literature by studying skewness risk premia on individual stocks and then focus on analyzing the cross-sectional variation of SRP. In particular, this paper estimates skewness risk premia on individual stocks using synthetic skew swaps and shows that there is a considerably large variation of monthly realized skewness risk premia across a representative set of portfolios which are sorted by skewness risk premium payoffs in the prior period. It then focuses on investigating the determinants of such cross-sectional variation and documents that consumption risk does not seem to be priced with respect to skewness risk premia. The market excess return and, especially, the market variance risk premium are shown to be key risk factors in the cross-sectional variation of average skewness risk premium payoffs. The market variance risk premium factor is significantly priced with respect to skewness risk premia even if I allow for potential model misspecification. The success of the market variance risk premium factor can be potentially explained by the very different risk exposures of skewness risk premium-based portfolios to the risk proxied by the market variance risk premium. I further show that the higher the exposure of the skewness risk premium-based portfolio to such a risk, the larger skewness risk premium payoff is required in the cross section.

In Chapter 3, I focus on exploring the relation between model-free stock implied moments and stock returns. Specifically, this paper builds an empirical model to connect option-implied cumulants with expected risk premia through latent risk factors. Expected risk premia on individual stocks are estimated by applying a new partial least squares-based method on risk-neutral cumulants at different orders and various maturities. The filtered expected risk premia based on the second and third order risk-neutral cumulants exhibit a considerably large dispersion across stocks, which further generates a wide cross-sectional variation in future realized risk premia. I find a positive relationship between the ex-ante filtered expected risk premium and future realized risk premium during the period of 1996-2017. A strategy that goes long (short) the decile portfolio with the largest (smallest) filtered expected risk premium yields a Fama-French-Carhart alpha of 1.06% per month (t-stat: 3.75). Moreover, I show that the predictive ability of the filtered expected risk premium can be potentially explained by informed trading driven by short-selling constraints.

In Chapter 4, I investigate the importance of higher moments of consumption risk in pricing cross section of stock returns. I propose and estimate through Bayesian methods a flexible parametric multi-factor asset pricing model in which the importance of higher moments of consumption risk is highlighted. The newly proposed estimation algorithm allows to simultaneously estimate preferences parameters associated with higher moments of consumption risk and parameters related to consumption dynamics such that the consumption dynamics are consistent with the cross sectional variation of stock returns.

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